Identifying Distracted and Inattentive Driving of Vehicles by Detecting Driver-induced Steering Oscillations

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Abstract

With the ongoing evolution of automobile technology, human errors have become one the most prominent factor of traffic accidents. The primary reason of these errors is inadequate cognitive load of drivers, in which the amount of the attention dedicated to driving is lower than the attention required by the current traffic situation. The most relevant symptom of inadequate cognitive load is the delay in response of a driver. In principle, we could infer the inadequate cognitive load by measuring directly the amount of delay of a driver's response to various environmental stimuli during driving, e.g., the delay of pressing the brake pedal in emergent situations. Such an approach, however, could not be used for early warning of the eventual inadequate cognitive load of drivers.

The objective of our research is to detect indirectly the delay of a driver's response as a symptom of inadequate cognitive load. In other words, the main objective of this study could be considered as identifying drivers' distraction and inattention in normal driving situation. Also, as an accident-preventive approach, the detection should be done in routine driving situations – such as (i) driving on a straight, (ii) entering- and (iii) exiting a turn.

In the proposed approach, we consider a driver as a controller of a system (car) with feedback. In addition to applying the feedback control theory, we imply that feedback delay would result in unstable, oscillating behaviour of the system. Focusing on steering of the car, we hypothesize that the feedback delay caused by inadequate cognitive load of drivers would result in steering oscillations. Detecting these oscillations would be crucial for early warning of inadequate cognitive load of drivers.

Moreover, we applied agent-based modelling in which an agent evolved via genetic programming, models the steering behaviour of a human driver in accordance with the servo-control model of the driver.

In our experiments, instead of relying on a real car, we use a car simulated in The Open-source Racing Car Simulator (TORCS). TORCS offers the advantages of being (as a software system) a crash safe, realistic (by modelling faithfully the laws of vehicle dynamics), open-source, and free of charge.

To verify our hypothesis that inadequate cognitive load would result in detectable steering oscillations, we conducted three different experiments. They were conducted for a routine driving (with constant speed of 50km/h) on a straight, entering- and exiting a corner: first, we comparatively analysed the steering behaviour of an artificial driving agent with instant and with artificially delayed (100ms, 200ms and 400ms) steering. Then, we experimented with ten different human drivers with instant steering and with steering, that is artificially delayed by 400ms. Finally, we experimented with the same ten human drivers subjected to naturally occurring (by texting) cognitive delays.

Experimental results suggest that both the artificially introduced and naturally occurring delays yield subtle, yet detectable oscillations in steering behaviour of both the driving agent and human drivers. These oscillations are manifested in characteristic dynamics of steering angle, and the resulting trajectory and lateral acceleration of the car. The power spectrum of Fourier transformed lateral acceleration signals indicates a well-distinguishable (from normal driving) frequencies and amplitudes of the driver-induced oscillations.

Additionally, we investigated novel approach on detecting these oscillations. First, we applied single threshold (based on spectrum analysis) in each situation for detecting steering oscillation. We further optimised our method by evolving the weight coefficients of power spectrum, in a way that oscillated signals (due to cognitive load) would naturally yield higher power spectrum than non-oscillated signals, via genetic algorithms. We further extended our study by examining individually adaptive threshold mechanism (based on the absolute value of lateral jerk). Finally, this mechanism was further tuned with feature identification and was implemented for real-time detection in fully-fledged driving simulator and tested in real-time by developing a smart phone application.

As a conclusion, our investigation shows that - well-detectable steering oscillations are induced as an effect of cognitive delays in human drivers and these oscillated signals could be well detected by our proposed methods. Further, the detection of these signs using our approach could be used for early warning of the eventual inadequate cognitive load of drivers.

We view the obtained outcome as a significant step towards the development of a more robust system for early-warning of the inadequate cognitive load of drivers in routine driving conditions – well before any urgent reaction to an eventual dangerous traffic situation might be needed.

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Chapter – 1

Introduction

1.1. Background

The innovations in embedded devices in transportation systems has revolutionized the world. These advancements have added both luxury and convenience by transforming limited space of a vehicle into a kind of mobile office. The advanced technologies in today's vehicles, such as lane detection, adaptive cruise control, navigation systems, wireless network connectivity, and real-time systems providing information about the traffic, road-conditions, weather, location-dependent points of interests (fuel stations, parking areas, restaurants, sightseeing spots, etc.), news, etc. are gradually becoming a standard for many of modern automobiles. With over 1 billion vehicles around the world [1] integrating these devices and technologies might well result in development of the intelligent transportation systems that could save our valuable time and tedious efforts. However, using these technologies while driving might prove to be a significant source of distraction for the driver, which, in turn might ultimately result in increase of the number of traffic accidents caused by driver's inadequate or slow response to urgent hazardous traffic situations [2].

1.1.1. Concept of Driver Inattention

Driver inattention is a prominent factor of traffic hazards. Most often, distraction is seen as a main reason for such inattention [3]. Distraction happens when driver shift their attention from the primary task of driving to secondary or even tertiary (unrelated to the driving) tasks [4]. The driver distraction is usually categorised in the four main types [5] [6]. (i) Visual distraction, occurs when driver looks away from the current road situation (e.g. looking at the map of navigation system, air-conditioner settings, etc.). (ii) Cognitive distraction, occurs when driver take off their concentration from driving to some other task (e.g., daydreaming). (iii) Physical or biomechanical distraction, induce because of biomechanical requirement of a driver to operate the secondary task, (e.g. operating the navigation system, air-conditioner, CD player, etc.). Finally, (iv) auditory distraction, is triggered by auditory signals from the external sources (e.g. in-vehicle conversation with passengers, hands-free conversation via mobile phone, etc.). Chapter 2 provides more detail discussion on models and definition of driver distraction and inattention.

Different types of distraction could be induced by different, independent sources and, therefore, multiple types of distractions could occur simultaneously. In a case of texting while driving, all of the above-mentioned distractions (visual, cognitive, physical, and auditory) might occur simultaneously. First, when message is received in a cell phone, driver might receive an auditory signal, which results in a corresponding auditory distraction. Then, driver looks away from the current road situation in order to check the contents of the received message, which implies a visual distraction. Driver becomes cognitively distracted when trying to comprehend the received message, and when thinking about the eventual response to the message. Finally, driver types a reply to the message, which results in biomechanical distraction. Therefore, texting while driving could be considered as quite dangerous case of inattention because it is usually associated with all types of distraction of the driver. In our work, we consider primarily the visual and cognitive aspects of the distraction caused by texting while driving.

Since, even the mere switch of attention - implying a cognitive multitasking (as in texting and driving) that the human usually does not excels at - leads to the disruption of the cognitive engagement dedicated to the primary task of driving. In such situations, the degree of attention dedicated to driving becomes considerably lower than that actually needed by the existing traffic situation. Such phenomena of disruption of cognitive engagement is often viewed as inadequate cognitive load (CL) of the driver. The concept is further elaborated in section 1.1.2.

1.1.2. Cognitive Load and its Impact while Driving

In cognitive psychology, cognitive load is defined as the total mental effort required to process information [7], and it is proportional to the amount of information perceived. This proportional relationship exists because higher cognitive load, which is associated with extended mental resources, is required to cope with the incoming flow of information. In the context of driving, we could rephrase the notion of cognitive load on the driver as the amount of attention of the driver, which are allocated for primary task of driving. An account on the theoretical model of mental workload could be found in the work of *Waard* in [8], where he discussed about various theoretical models of mental work-load, task performance and demand. His work also evaluates different concepts of mental workload, which are linked to the mental workload based on applied psychological experiments.

In this study, we use the phrase, "inadequate cognitive load," and "cognitive load" interchangeably to describe situations (i) in which the driver allocates too little attention to driving (i.e., cognitive underload), or (ii) when the cognitive resources required for comprehending the current driving situation surpass the natural limits of the mental resources of the driver (i.e., cognitive overload). We have categorized the following two cases of inadequate cognitive load while driving:

1.1.2.1. Cognitive Underload

Cognitive underload might occur while driving on a deserted or low-traffic highway. Normally, in such a situation, the attention required by the current traffic environment is much lower than the available cognitive ability of the driver. Often in such circumstances, the driver allocates too little cognitive resources to their primary task of driving, with the reduced attentiveness often resulting in mind wandering [9] or even micro naps (brief naps lasting between 0.5 and 1.5 seconds). The condition could become worse depending on the incorporated safety facilities that either assume part of the task of driving the vehicle (e.g., lane following or adaptive cruise control) or, at least, induce an inflated sense of safety in the driver (e.g., anti-lock braking system, traction control, electronic stability program, collision warning, or blind spot warning).

This results in the inability of the driver to swiftly allocate the required additional cognitive resources should an extreme traffic situation present itself (e.g., changing lane on a busy expressway or, suddenly slowing down because of the car(s) ahead, approaching or leaving tollgates, or joining a busy intersection after leaving the expressway). In addition, apportioning the necessary cognitive resources might be more severely affected if the spare mental resources of the driver were allotted to tasks that are distinct from driving or to secondary tasks such as texting, talking on the mobile phone, eating, drinking, using the navigation system, or simply talking to passengers [10].

1.1.2.2. Cognitive Overload

The case of cognitive overload is triggered while driving in congested traffic or uncontrolled intersections. In such a situation, the mental processing ability required by the existing surroundings might surpass the cognitive ability of the driver. It might temporarily occur when a driver who experiences temporal cognitive underload faces an urgent hazardous traffic situation, as we mentioned above. In addition, a longer-term cognitive overload might be witnessed in elderly drivers as a result of the natural gradual decline in their mental abilities. Moreover, these reduced abilities might even cause moderately fast-moving traffic to be subjectively perceived as being much faster or more intensive than it actually is which is also termed as cognitive slowing. As a result, the prevailing “looked-but-failed-to-see” accidents at busy intersections are often triggered by cognitively overloaded (elderly) drivers [11].

Therefore, an eventual early identification of the above-mentioned two cases of inadequate cognitive engagement might prove to be vital for the prevention of traffic accidents.

1.2. Objective of Research

The core objective of this research could be summarized in following points:

- To verify that cognitive load in human drivers results in the delay of response of the driver.
- To verify that the delay of response due to delay in feedback result in steering oscillation of the car.
- To propose the method to detect steering oscillation of a car as a mechanism to prevent accidents before they actually occur.

1.3. Motivation of Research

This work is motivated by the following two major factors. First, regardless of the substantial amount of research available on the consequences of the psychological aspects of drivers on road traffic safety [5] [2] [8] [11], such as an inadequate cognitive engagement, there is still a very limited amount of work available on the implications of these factors on the emergent dynamics of the vehicle. For instance, *Waard* [8] has presented various methods for measuring the mental workload of drivers. However, the presented measures are either more subjective (self-reporting measure, TLX, SWAT, or physiological measurements) or could not be used for inferring the inadequate cognitive engagement, and eventually – alerting the driver in real time because of lack of reliable devices and sensors (standard deviation from centre of the line, nonlinearities in steering angle etc.). Some work on steering entropy [12] also tries to visualize the effect of cognitive load in steering behaviour of the driver. The method is based on analysing the time-series of the steering angle of the car, while the practical implementation of the sensors that could register this angle is challenging. On the other hand, a sensor placed on the steering column that measures the steering wheel angle could be used instead, but relatively few models of cars are currently equipped with such. In addition, due to the inevitable hysteresis caused by the mechanical plays in the steering system of the road cars, the pattern of the steering wheel angle do not necessarily mirror the pattern of the actual steering angle of the front wheels of the car. In addition, conversely to our approach, which considers the effects of well recognized cognitive delays on vehicle dynamics of the car, the entropy-based metrics could not be convincingly explained from the biologically plausible point of view.

Second, despite the existence of well-known related research in aviation on the phenomena known as pilot-involved- and pilot-induced oscillations [13](i.e., uncontrollable oscillations in pitch angle or angle of attack of the aircraft), we are not aware of any research that considers steering oscillations to be a direct consequence of inadequate cognitive engagement in drivers. Conversely, studies on pilot-induced oscillations usually consider the cumulative effect of two factors—high sensitivity and late responses of digital fly-by-wire aircraft control systems to pilot input.

Other, important motivation of this research is explained from the perspective of real world application. The driver distraction is one of the major problems in the world today, which is also an indispensable source of driver inattention. In USA alone, 3,477 people lost their life and 391,000 were injured in 2015 on various automobile-related crashes that involve some form of distracted driving [14]. In addition, this is increasing with time and new devices. Therefore, if only we could devise some system (hardware, software or both) this numbers could be significantly reduced if not completely eradicate. Hence, one of the important motivation of this research is its application in the real world situation that could not only help to alert people when distracted but also contributes on preventing accidents that incurred due to driver inattention and distraction.

1.4. Limitation and Challenges

This work has been performed under the strict laboratory settings. Moreover, the initial investigation was accomplished on the experimental data that were recorded on the low-end driving simulator. However, towards the end of this study we tried to test the robustness of our approach by experimenting (i) on fully fledged driving simulator and, (ii) on real-car driving under strict environment (because of safety issue) (more detail in Chapter 10). Beside this, since experimenting on real-car within real scenario was literally impossible due to legal issue, robustness of this research has not been tested in the real environment with multiple human drivers.

In addition, it is very challenging and bit difficult to comprehend the impact of subject factor that are often biased during data collection. We tried our best to reduce such impact by informing and making our subject aware of various human-related issues. However, we could not fully neglect the fact that some form of subjective bias might have influenced our dataset.

1.5. Thesis Outline

- **The Model of Driver Distraction and Inattention (Chapter-2)**

Chapter 2 of this thesis discuss the definitions of inattention and distraction based on various literatures. This chapter also discuss the model of human cognitive process and various forms as well as sources of distraction.

- **Hypothesis Formulation (Chapter-3)**

Chapter 3 discuss the main idea of our study. This chapter discuss about driver in the control feedback loop and highlights some major component with the model of system where human driver acts as the controller of the feedback control system. Around the last section of this chapter, we have also defined our hypothesis.

- **Research Framework for Hypothesis Testing (Chapter-4)**

This chapter discuss about the framework used in our study. It also include detail description about driving simulator, experimental setups and different test conditions. Chapter-4 also shades light on evolutionary computation and our in-housed XGP, which was designed for implementing Genetic Programming and Genetic Algorithms. It also explains the model of our driving agent that was evolved via XGP.

- **Hypothesis Verified; Steering Oscillation as the Effects of Delayed Response of the Driver (Chapter-5)**

Chapter -5 presents multiple experimental results, to verify our hypothesis. The experimental result with driving agents and with real human driver has been discussed in this section. It shows various results relating to the occurrence of steering oscillation.

- **Proposed Method for Oscillation Detection (Chapter-6)**

Chapter-6 highlights on our proposed model of oscillation detection. It discusses the methodologies and result on classifying oscillating (inattentive) and non-oscillating (attentive) driving case. Further, it also present some limitation of the proposed model and discuss possible solutions.

- **Enhancing Proposed Method via XGP (Chapter-7)**

Chapter-7 presents some experimental results and discussion on enhancing the proposed model with XGP. It talks about some limitation on the proposed model and highlights how those limitations were resolved using XGP.

- **Individually Adaptive Method for Oscillation Detection (Chapter-8)**

Chapter-8 further extend the enhancement of the proposed model by introducing mechanism that could adapt with the individual driver and the driving conditions. It discuss about the adaptive model and present experimental result for the classification of attentive and inattentive driving conditions.

- **Real-time Implementation of the Method (Chapter-9)**

Chapter-9 will provides new direction to our study, as it propose various feature of steering oscillation. This chapter presents details on how those features were detected in real time implementation. Here first section presents our real-time detection model and some experimental result that were tested on fully fledged driving simulator, while other section focus on the mobile application.

- **Summary, Conclusion, and Future Work (Chapter-10)**

Chapter-10 is the last chapter of this thesis. This chapter present the summary of our study, some of our achievement and conclusion, and finally ends by discussing possible direction of this research.

Chapter - 2

The Model of Driver Distraction and Inattention

2.1. Definition of Driver Distraction and Inattention

2.1.1. Driver Distraction

Driver distraction and inattention is one of the most common topic that we can find in the literature that deals with the human factor for automobiles, traffic accidents, and accident prevention or even in intelligent transportation systems. Often, we find this two term used as a substitute of one another to deliver the meaning usually referring driver being inattentive, that could in fact mean driver getting distracted but it could also be used to refer driver being inattentive due to, for example, mind wandering. Therefore, the meaning of these two term varies upon the context and literature.

Starting with the literal meaning of distraction, the online version of oxford dictionary has defined the term distraction as “Prevent (someone) from concentrating on something; Divert (attention) from something; Divert one’s attention from something unpleasant by doing something different or more pleasurable”. While this definition from the oxford is more diverse in terms of context we put it through, M. Regan and his colleagues in their paper [4] tries to formulate a generally accepted definition especially in context of *driver* distraction and referring to the paper of *Hedlund et. al* [15], they define driver distraction as;

"a diversion of attention from driving, because the driver is temporarily focusing on an object, person, task, or even not related to driving, which reduces the driver's awareness, decision making ability and/or performance, leading to an increased risk of corrective actions, near-crash, or crashes".

Likewise, more comprehensive definition has been forwarded by *Pettit et.al* [16] as follows;

"Driver distraction:

- Delay by the driver in the recognition of information necessary to safely maintain the lateral and longitudinal control of the vehicle (the driving task) (Impact)
- Due to some event, activity, object or person, within or outside the vehicle (Agent)
- That compels or tends to induce the driver's shifting attention away from fundamental driving tasks (Mechanism)
- By compromising the driver's auditory, biomechanical, cognitive or visual faculties, or combinations thereof (Type)"

Moreover, *Lee et. al.* [17] has rather provided a very simple definition in their work, which says, "Driver Distraction is the diversion of attention away from activities critical for safe driving towards a competing activity". However, more different version of definition could be found in the work of *Treat and Hoel* [18] [19], which are more context specific.

However, for the purpose of this work, we define driver *distraction as the shift in the attention of the driver, from the primary task of driving to secondary or even tertiary (unrelated to the driving) tasks* [4].

2.1.1.1. Forms of Distraction

Distraction could be further differentiate in four or five different forms that are discussed below;

2.1.1.1.1. Visual Distraction

The type of distraction that occurs while looking away from the road for a non-driving-related task from the current driving task could be considered as visual distraction. Visually induced distractions are the common type of distraction that occurs every day when we are driving. Distraction from navigation display, text-messages, billboards around the road, pedestrian, etc. are some of the common example of visual distraction.

Additionally, in the literature [20], we could find that visual distraction could be further divided into three different types. The first is where the driver's visual field is blocked i.e. where he should be looking while driving for example, the front-side or rear of the vehicle. The second he discuss is the visual distraction where the driver neglects to look at the critical areas, focusing instead for some period on another visual target, which creates safe driving issues. The third is when the driver is distracted and his attention wanders from his driving. Any of these three types of problems can impede safe driving and have long been restricted by some form of law.

2.1.1.1.2. Cognitive Distraction

The type of distraction that occurs while the driver takes off their mind out of the road in the process of attending the conversation with their passengers, talking on the cell phone, or simply getting mind off the road due to daydreaming or mind wandering – rather than considering the current traffic situation.

Cognitive distraction seems to have much diverse definition and understanding. Literature suggest that studies [21] related to cognitive distraction are much more inconsistent in their definition. For instance, some definitions do not include cellular conversation, while others do. Some definitions confound cognitive distraction with visual distraction, or cognitive distraction with cognitive workload. Other studies define cognitive distraction in terms of a state of the driver, and others in terms of tasks that may distract the driver. It is little wonder that some studies find that cognitive distraction is a negligible factor in causing crashes, while others assert that cognitive distraction causes more crashes than drunk driving. Therefore, in this study we consider cognitive distraction as *the shift in the mental process due to driver's engagement in various secondary or tertiary activities*. In addition, this study assumes that with the occurrence of every other type of distraction, there is some form of cognitive distraction taking places in our mind. This is because every distraction would shift the attention of the driver that would ultimately alter the cognitive process of human mind.

2.1.1.1.3. Physical (Biomechanical) Distraction

The type of distraction that is induced when the driver physically engage on other activities then the primary task of driving is known as physical distraction. The driver is said to be in physical distraction when, the driver holds or operate a device rather than steering with both hands, or dialling, on a mobile phone, or leaning over to tune a radio to adjust the volume or change the music that may lead to rotating the steering wheel.

2.1.1.1.4. Auditory Distraction

The distraction that occurred because of loud sounds are often categorized as the auditory distraction. The distraction from the ringing mobile phone or its vibration, loud volume of in-vehicle devices like CD players, or even the loud noise of in vehicle passengers that would mask other sounds are the example of auditory distraction.

2.1.1.2. Sources of Distraction

As the sources of distraction has been briefly mentioned in the previous section in terms of examples to various forms of distraction, in this section, those sources of distraction are further categorized into two different types. They are (i) Internal distraction and (ii) External distraction.

2.1.1.3. Internal Distraction

Internal distractions are the distraction that incurred due to various devices or persons residing in the car. It is also known as in-vehicle distraction. The few example of in vehicle distraction could be a very basic activities like drinking, eating, talking to a passenger as well as engaging own self with on-board entertainment systems like CD player, Radio player etc. [22] [23]). However, with the miniaturization of new electronic components, various electronic devices have now become the most common part of automobile system that plays significant role in compromising the road safety. These electronic devices are either included in the car or could be separate portable devices like smart phones, portable music players, tablets or other information devices like navigation system integrated with Global Positioning System (GPS). While the significance of such systems like navigation, systems and intelligent speed adaptation (ISA) systems could not be neglected but they are also highly responsible for various in-vehicle distraction. Internal sources of distraction also include the growing number of communication technologies that are now integrated into vehicles – for example, the Bluetooth, Wi-Fi, or infrared technologies and those that allow drivers to access their e-mails and Internet. Some studies show that using in-vehicle entertainment systems has detrimental effects on driving performance [22]. Indeed, adjusting a radio, CD or cassette player was found to be one of the major causes of distraction-related crashes in the United States and while information on newer technological sources of distraction is lacking, it is likely that negative effects on safety would be expected. Hence, some of the main internal source of drive distraction could be as follows [6]:

- Adjusting temperature controls
- Adjusting radio, CD
- Dialling or texting on a mobile phone
- Eating or drinking
- Moving an object in the vehicle
- Talking to other vehicle occupants
- Smoking
- Using a device or object integral to the vehicle (e.g. speed adaptation system)
- Using a device or object brought into the vehicle (e.g. Blackberry, iPod, laptop computer, etc. [23]

2.1.1.4. External Distractions

External distractions are the distraction that incurred due to various things located outside the car. High raised appealing buildings, attractive billboards, people and pedestrian are few source included in external distraction. However, with the technological advancement, there has been many efforts to design the billboards and advertisement on the road. Such design are developed in such a way that it would be impossible to avoid looking at, like video advertisements, neon and led based billboards etc., which possess more threat to the driver safety and are the indispensable source of driver distraction. Also because a study comparing the distraction to drivers caused by static versus video billboard advertising found that video adverts had a more detrimental effect on driving performance, suggesting the increased risk of this form of external distraction to safe driving [24].

2.1.2. Driver Inattention

In literature, inattention has often been defined with the definition of attention. Hence, a good step would be to start with the meaning of attention. The online version of oxford dictionary has demarcated attention as "Notice taken of someone or something; the regarding of someone or something as interesting or important; the mental faculty of considering or taking notice of someone or something", which is again so much generalized and more context specific. However, a very nice definition of attention has been recorded by the *nature.com* [25]with the more realistic essence which says, "*Attention is a cognitive process in which a person or animal concentrates on one thing in particular. To attend to something is to focus, heed or take notice of that thing irrespective of what else is going on in the surroundings*".

On the other hand, inattention is defined as "Failure to attend to one's responsibilities; negligence" by the oxford dictionary. However, in context of driving, *Victor et. al,* [26] has defined it as "improper selection of information, either a lack of selection or the selection of irrelevant information", which is well cited by Regen in their paper [4]. The other definition mention in Regan's paper include that of *Craft & Preslopsky* [27]. They defined driver inattention as event that occurred when the driver's mind has wandered from the driving task for some non-compelling reason which could be like, when the driver is focusing on internal thoughts (i.e. daydreaming, problem solving, worrying about family problems etc.), and not focusing attention on the driving task". While, *Klauer et. al* [28] has defined driver inattention as " any point in time that a driver engages in a secondary task, exhibits symptoms of moderate to severe drowsiness, or look away from the forward roadway" which combines both the activity and state of the driver.

2.2. How Different are Driver Distraction and Driver Inattention?

It is a topic of debate when we try to unfold our understanding on if the driver distraction is different from driver inattention. However, following the literature, driver distraction is generally thought to be different from driver inattention, or poorly allocated attention [3] [6]. Distracted driving occurs when some kind of triggering event external to the driver results in the driver shifting attention away from the driving task (e.g. a ringing mobile phone). Thus, the diversion in attention occurs because the driver is performing an additional task or is temporarily focusing on an object, event or person not related to primary driving task [15]. Inattention while driving applies to any state or event that causes the driver to pay less attention to the task of driving – the inattention can be present without necessarily having been triggered by an event, for example, daydreaming [5] [29]. The diversion of attention that occurs in distracted driving is also distinct from those impacts on driving performance that are attributable to a medical condition, alcohol or drug use, and/or fatigue (although these factors may compound the effects of distraction).

However, if we look into the fundamental aspect of distraction and inattention they are similar in a sense that both causes the driver to pay less attention to the primary task of driving irrespective of the how the event was triggered. And, as the effect is same the things that incurred inside our brain during distraction and inattention is also same. This study follows the understanding that distraction is some form of inattention and both of the word in this study are used to provide the meaning of driver being inattentive without considering if its triggered by some external event or not. The following sub-section give brief explanation on what happens inside the inattentive (distracted) brain.

2.3. Inattentive Driving: What Happens Inside the Distracted Mind?

Human brain is one of the most fascinating organ that evolution has ever gifted to the humanity. This makes us cognitively superior among other creatures in the world. Being said that, it is also among the most little understood organ. For instance, its complexities could be infer from the reference that, our brain contains 100 billion neurons. Also, these number are 10 times higher when the count comes to glial cells (non-neuronal cells that maintain homeostasis, form myelin, and provide support and protection for neurons in the central and peripheral nervous systems [30] [31] [32] [33]). However, we must accept the fact that there are no original references about how those number emerged in any of the journals available today [34]. Like any other parts of our body, human brain is also constantly evolving and is responsible for comprehending various cues that we perceive through our senses. But, despite being such a sophisticated organ of our body, human brain still lacks the capability of multitasking [35] i.e. instead of handling the multiple task in parallel, our brain is evolved to handle them in a sequential fashion. Our brain does so by switching between the tasks rapidly and performing only one task at a time. Furthermore, brain also constantly engage in processing the information that it receives from different sense organs. It has to receive process, encode and execute that information. However, when the brain engage in processing the information received from multiple source it is overloaded with the information that would increase the cognitive load, which results in delay of response or say increases reaction time. The following Figure 1 shows the information processing chain in general.

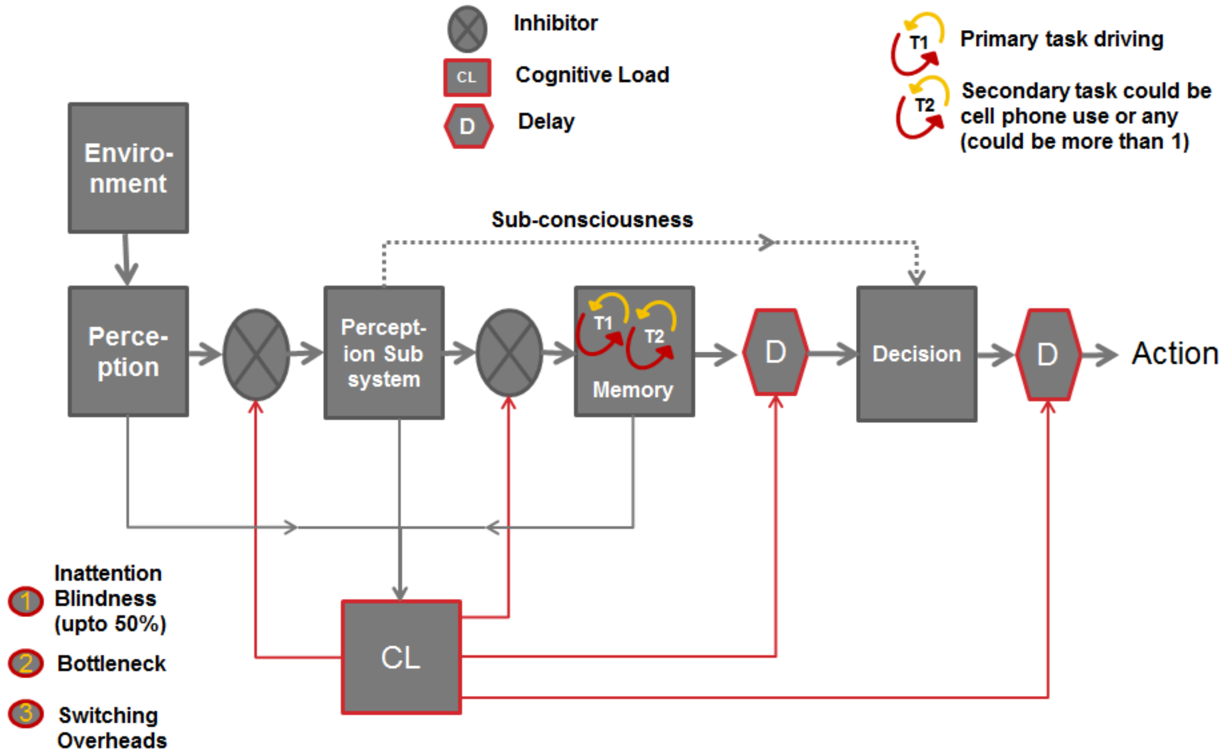

Fig-1: Basic architecture of human information processing (decision-making)

The above figure shows the basic information processing chain in human mind. In a very general scenario i.e. without inattention or distraction, human driver perceive different cues or information from the environment while driving. These cues could be anything from, traffic lights, traffic signals, pedestrian, horns of other vehicle, sound of other vehicles, etc. Since, driving is a very complex task, which requires immediate and constant feedback from the driver, who has to maintain minimum level of cognitive load that could be handled by the human brain so that there is no delay in intermediate information processing chain. Moreover, when this visual, verbal, or other cues reached to the perception sub-system, different unit of the brain starts processing them. In the process some cues are subconsciously mapped to the memory and after information encoding and retrieval, the decision is made. While other has to consciously go to the various region of the brain and after information encoding and retrieval decisions are made and action is performed.

However during inattentive driving induced by the distraction or other sources, driver has to instantly deal with huge amount of information either from the primary task of driving, or from the distracting sources (like texting). Since cognitive resources could not be extended nor are capable of multitasking, such overloaded information would increase the amount of cognitive load in the perception sub-system, which might ultimately create cognitive bottleneck in the perception system as well as increase the switching overhead while associating perception signal from multiple task to different regions of the brain. In addition to increase in switching overhead, performing a secondary task (such as texting or messaging) while driving also results in inattentional blindness where the information perceived from the primary task (driving) are not mapped to corresponding region of the memory to encode and/or retrieve the information. So all these factor would delay the information processing chain in driver's brain, which as a whole increases reaction time of the driver as well as delay their action. In the shown in Figure 1, the thick arrow line shows a basic information flow, thin arrow shows the possible areas affecting cognitive load (CL) and red thick line from the CL shows the effect of cognitive load in various part of information processing chain.

2.4. Review of Driver Assistant and Monitoring Systems

Mobility is the important aspect of modern world, in that, vehicles and drivers are the two key elements. There has been much research work done to optimise these two elements in mobility. These might be the reason why very few accidents happens due to the mechanical failure of the vehicle, however, these number are increasing everyday if count the human factor side. Driver Assistant and Monitoring Systems (DAMS) is playing important role in reducing the number of traffic accidents around the world. New research in the field of automobiles and vehicle have given birth to numerous such systems, which is now a necessity of a modern automobile. Reviewing the evolution of assistant system, we could divide them into three different phases based on sensors, functions and their goals [36], which are further discussed below and are summarized in Figure 2:

2.4.1. First Generation Assistant Systems

Initially introduced DAS are mainly based on measuring the internal status of the vehicles, such measurements included velocity, acceleration, or both and measurements were acquired mostly from proprioceptive sensors (sensing internal state). These systems focuses much on maintaining stabilization of vehicle dynamics. The development of Anti-lock Braking System (ABS) in 1978 (Bosch), Traction Control System (TCS) and Electronic Stability Control (ESC) marked the first milestone development of Driver Assistant Systems.

2.4.2. Second Generation Assistant Systems

The assistant systems that are introduce after 1990 are highly based on exteroceptive sensors (sensing external state). These systems focuses on providing information and warnings to the driver, and on enhancing driving comfort. The development of Navigation System, Park Assistant System, Forward Collision Prevention System, Adaptive Cruise Control System, and Lane Departure Warning System are few of the noted milestone for advanced driver assistant systems.

2.4.3. Third Generation Assistant Systems

The assistant system that are presented or elevated after 2012 are vastly centred on complex network of both proprioceptive and exteroceptive sensors. These systems efforts on providing automated and cooperated driving services. Some of the partially implemented driver assistant system in this category are low-speed automated driving, automated highway driving, multisensory platform etc.

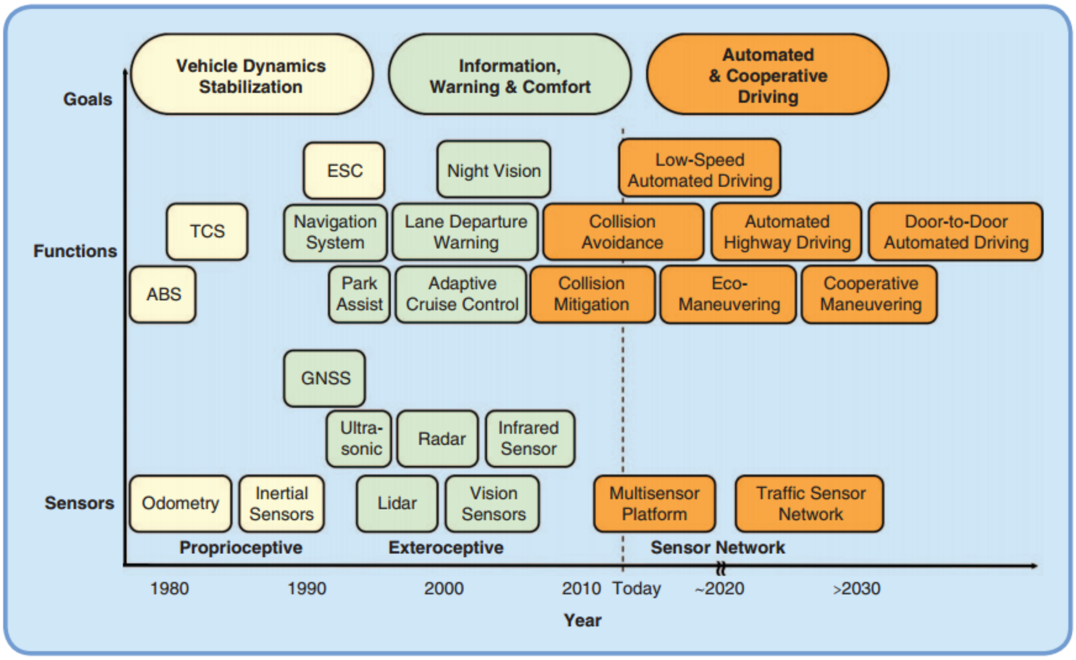

Fig-2: Past and Potential Future Evolution in Driver Assistant System [36]

On the other hand, Driver Monitoring System (DMS) is also one of the dynamic field of research. There are different methods that are implemented for DMS. The most common method of DMS is biological signal processing where various biological signals such as ECG, EEG, EOG etc. are monitored, recorded and analysed using machine learning algorithm to determine the driver state [37]. Similarly, various image base technique are also used to monitor driver using visible spectrum camera, IR camera, and stereo camera [38]. Some system are also based on pupil dilation measurement to determine the cognitive overload of the driver [39]. However, these systems are based on sensors where driver has to involve directly for the measurement and small deviation from the sensors range might increase the chances of false alert significantly. In addition, driving is a subjective behaviour, using the same system without adapting mechanism might not yield better result. Conversely, we proposed to use accelerometer as a sensor to analyse the effect of cognitive load in steering behaviour of the car, which in no way required driver to be in the sensing range. Some other research like steering entropy [12] studies the cognitive load based on the signal of steering angles however, it has some limitations (mentioned already in motivation section). Honda's wobble driving judgment algorithm (English Translation) also tries to detection the oscillation of the car [40]. This algorithm consider central reference line from the trajectory and lateral deviation to detect the wobble of the car with reference to the angular velocity. However, we would be unable to detect reliably the inattentive driving from deviation of the central line. Indeed, a fully attentive driver might deliberately "wave" across the lane in cornering (entering from outside, moving to the inside at the apex, and exiting from the outside), may circumnavigate obstacle, rough road, bicyclist, or, simply, may not mind driving slightly off the middle of the lane. We believe that it would be difficult to discriminate these cases of attentive driving from oscillations caused by DoR of the driver without an appropriate spectral (frequency-related) analysis of the relevant parameters (deviation from centreline, steering angle, lateral acceleration, etc.) of the moving car.

2.4. Discussion

The combination of continuous technological progress of automobile systems, ever rising density of the traffic, and increase in the speeds of vehicles has made the driving more challenging and more dangerous than ever before. There is no doubt that the advancement inside a cockpit with a miniaturization of aided technology and handheld devices has added comfortability but with a price of potentially dangerous distraction of the driver. Also, distraction happens due to limited ability of our mental resources to process the information. Human brain is not made to process multiple task and switching cost between the task are higher, therefore, limited resources get overloaded with the flow of information and higher switching cost, that might result in inadequate cognitive load of the driver.

Identifying inadequacy of driver cognitive load could be crucial towards prevention of many driving accidents. The common symptom in both aforementioned scenarios of inadequate cognitive load is the delayed response of the driver. Therefore, in principle, we could infer inadequate cognitive load by directly measuring the amount of delay in drivers' actions to various environmental stimuli during driving – such as the delay in pressing the brake pedal in various emergencies. Such an approach, however, would suffer from the following two drawbacks:

A delay in response during normal driving is a personal trait, and some drivers may respond slowly just because they are sure that the current conditions of the road, car, and driver do not require an urgent response. According to the risk homeostasis theory [41], drivers tend to engage in a riskier driving style when extra safety measures or driving aids are incorporated in their cars (e.g., airbags, anti-locking brake system, traction control, electronic stability program, tires with better friction coefficient in slippery road conditions, etc.).

A delay in the response could be a meaningful indication of cognitive load only when measured directly in situations that really require an urgent response – such as a moving obstacle that appears suddenly and within close range of the car. Inadequate cognitive load in such a situation could indeed result in a delayed response by the driver, which in turn could result in an accident. Therefore, a delay in the response in such situations could not be used to provide crash-preventive early warnings with respect to eventual inadequate driver cognitive load. Hence, we need a novel and reliable method of detecting inadequate cognitive load of driver.

The next Chapter discusses the detail about the proposed hypothesis, which provides the fundamental assumption regarding our main ideas.

Chapter -3

Hypothesis Formulation

3.1. The Main Idea of Research

The brief theoretical review on the concept of cognitive load, and discussion on the model of information flow in previous chapters, has provided us the enough background on defining our hypothesis. The core concept of this study depends on driver in the control feedback loop, which is further elaborated in following subsection.

3.1.1. Driver in the Control Feedback Loop

The main idea of our research is based on the consideration of the human driver as the controller of a system with feedback. Therefore, assuming the human driver as the controller of the system (i.e., car) with a negative (i.e., error-correcting) feedback, we could illustrate the architecture controlled system as shown in Figure 3.

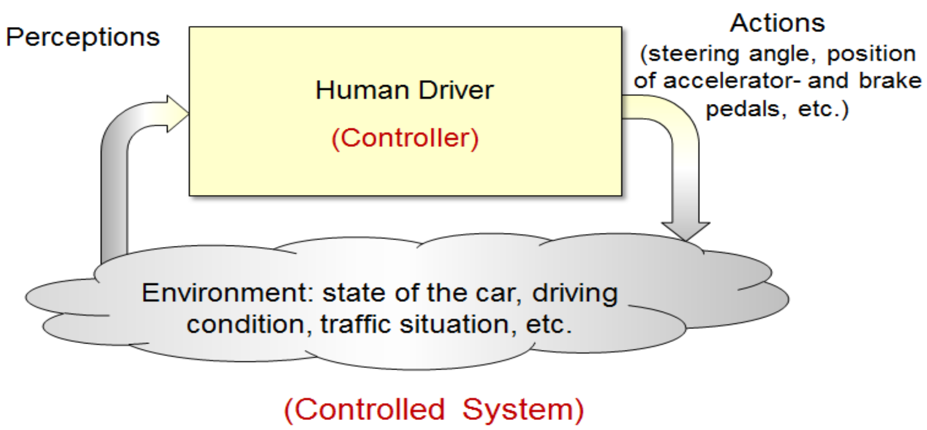

Fig-3: Human driver in the control feedback system

Figure 3 shows driver in the feedback loop of control system. The latter consists of four major component: (i) Environment, (ii) Perceptions, (iii) Controller/Decision-making and, (iv) Action.

3.1.1.1. Environment

Environment is the external world where driver observes and interacts with their actions.

3.1.1.2. Perceptions

Driver constantly perceives various cues from the environment. Perception are the inputs for the decision-making. There could be lots of perception cues in the environment (for example) - state of the car, driving conditions, traffic lights, traffic situations etc., which represent, basically, the feedback for the control system (car).

3.1.1.3. Decision Making

Human driver who acts as the controller of the system makes the decision regarding the actions they have to execute. Decision-making is done based on the perceptions input, i.e., the feedback.

3.1.1.4. Action

Action implies the mechanism on how the human driver affects their world (environment). Driver constantly receives feedback from the environment as a perception signal, makes correction in their decision, and then executes them via action signals. Generally, steering angles (control), pressing the accelerator or brake pedals to a certain degree, etc. are the actions that driver executes to affects their surroundings.

3.2. Hypothesis Defined

We have known from the explanations presented in Chapter 1 and Chapter 2 that inadequate cognitive load in human's cognitive processing chain or information processing chain would result in delay of response or increased response time. Considering human driver as the controller of the control system (car) with constant perception input (feedback) from the environment, such delay in response would result in the delay in feedback. Considering Nyquist criterion, we hypothesized that any delay in feedback would result in potentially unstable or oscillating system. Nevertheless, the question remains on which parameters would oscillate or in other words what would be the symptoms of delay of response in the driver in a loop system. The answer could be found in the parameters of actions that a driver performed to affect their environment, especially – those actions that are pertinent to a tracking behaviour of the controller (human driver). The oscillations in systems with feedback occur only if the behaviour of their controllers could be as a tracking one. The most common action the driver conveys to the car (as a control system) could be (i) dynamics of steering, (ii) dynamics of brake pedal (for decelerating) and, (iii) dynamic of accelerator pedal (for accelerating, cruising, decelerating), respectively. However, neither accelerating, cruising nor decelerating could be seen as tracking behaviours because the parameter, controlled by these behaviours – the speed of the car – is, usually controlled within a quite relaxed range of values. Conversely, steering control could be considered as a tracking behaviour where driver constantly tries to compensate the negative feedback from the environment in order – according to the servo control model of steering – to keep the lateral and angular deviation of the car from the canter of the lane minimal. In addition, it is recognized in aviation [13] that oscillations usually occur only in tracking behaviour. We can observe this in a phenomenon called pilot-induced oscillation where the oscillations of pitch angle (and angle of attack of the wing) of airplanes occur due to delayed feedback (rate limits) during landing or mid-air refuelling. *We focus on the control of steering of the car, because it manifests the only tracking behaviour during driving, and hypothesize that any delay in the feedback (e.g., caused by inadequate cognitive load of the driver) would result in detectable steering oscillations.*

3.3. Summary

The underlying idea behind this study is that, we consider human driver as the controller of the car (system) with negative feedback. In a control system with feedback, any delay in such feedback would result in potentially unstable or oscillating system (Nyquist criterion). Since we know from neuroscience that cognitive load would result in delay of response in information processing inside the human brain (refer to Chapter 2), and as human driver act as the controller of the system (car), we hypothesized that any delay in the feedback control would result in an oscillating system. In other words, we are interested to verify our hypothesis that the cognitive load in human driver would result in steering oscillation of the car. Hence, we proposed an original methodology to verify our hypothesis. The proposed methodology relies on various tools and software frameworks, which are further discussed on chapter 4.

Chapter - 4

Research Framework for Hypothesis Testing

This chapter discuss and explains different research framework, tools, and technologies that have been utilized in our research. Brief introduction on all the tools that were implemented for validating the research hypothesis has been provided in this section.

4.1. The Simulator

4.1.1. Software

We initially used software simulator called The Open Racing Car Simulator (TORCS) [42] as the driving environment to accumulate test data and validate our hypothesis. Our decision to perform the experiments using a simulated car instead of an actual car is justified by a combination of the following advantages of TORCS:

1) Level of realism of simulation of car dynamics,
2) Crash-proof (software) implementation of the car,
3) Computational efficiency, and

4) Openness.

The latter allows us to modify the code, the characteristics of the car, and its environment to suit our needs. However, being a software simulator, TORCS still features the reality gap compared to actual driving environments. It is also difficult to model various physical loads (caused by both longitudinal and lateral accelerations of the car) that would have been applied to the driver while driving an actual car in various real-world conditions. We acknowledge that this might cause some concerns regarding the validity of the obtained results. The indication of the credibility of our results could be seen, however, in the analogical research in aviation as discussed in previous chapters. This suggests that pilot-involved oscillations occur because of delays in the control loop (often caused either by rate limits of actuators of the control surfaces, or by the software of the fly-by-wire control system) of real planes. It is however regardless of the fact that the pilots are, indeed, engaged in piloting the actual plane and are, consequently, subjected to actual physical loads. In addition, we consider our current work on simulated car just as a first – yet an efficient, inexpensive, and safe – step towards the verification of our concept. As a next step, we could also replicate the experiments in real cars driven in real-world situations.

- **The Car**

TORCS provides flexibility to use the collection of inbuilt cars what are realistically simulated as per the law of physics. Besides that, the custom designed car could also be integrated in the TORCS system. We used the CLK DTM car for our entire experiment. The design of the car is shown in Figure 4, while its parameters are given in Table 1. For the purposes of continuity and comparability, the model of the car used in our experiments is kept same throughout our entire experiments in the research.

Fig-4: The simulated car in TORCS (i) Backward view (left), (ii) Top-Frontward view (middle) and, (iii) Sideward view (right)

Table-1: The feature of simulated car

Feature	**Value**
Model	CLK DTM
Length, m	4.76
Width, m	1.96
Height, m	1.17
Mass, kg	1050
Front/rear weight repartition	0.5 / 0.5
Height of centre of gravity, m	0.25
Coefficient of friction of tires	1.2
Drivetrain	front engine, rear wheels drive

- **Test Track and Test Case**

Along with the flexibility of various car options, TORCS also provides adaptability to use inbuilt and customized track for the driving environment. We use the track design as shown in the Figure-5. We also setup three different test cases for validating the hypothesis in the experiment i.e. (i) driving on a straight section of the track, (ii) driving on corner entry section, and (iii) driving on corner exit section.

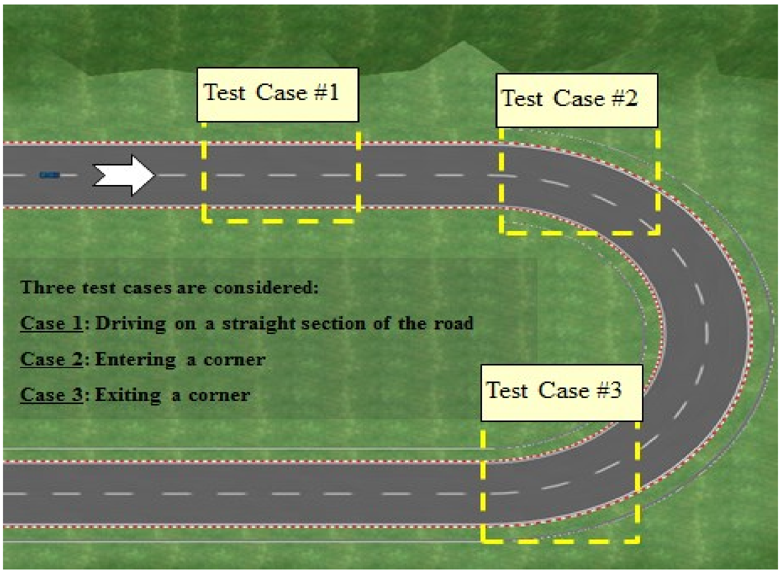

Fig-5: TORCS customized track design used in the experiment with three different test cases.

4.1.2 Hardware

In addition to the TORCS, we also used the Logitech Driving Force GT [43] gaming device as our hardware apparatus for steering wheel and, brake and accelerator pedals, to control the car. This hardware pieces was designed for gaming purpose (especially racing) for windows system that also maintains compatibility with PlayStation®3 system, and PlayStation®2 system. Its main feature includes advanced force feedback with 900 degree wheel rotation i.e. turns 2.5 times around lock to lock. The more important feature is its custom adjustment of both brake bias and traction controls, as well as steering movement for more realistic experience of driving (or racing). The pictures illustrated in Figure 6 shows the component of the Logitech's driving force GT. This device act as play, plug in window's system, and could be simply connect via USB to Windows PC and other compatible devices.

Fig-6: Logitech Driving Force GT steering wheel with various control buttons (left), and brake and accelerator controller pad (right)

4.1.3 Fully Fledged Driving Simulator

In addition to the TORCS, we also tested some of our proposed approach in fully-fledged driving simulator. We used the integrated system developed by FORUM 8 Co. Ltd [44]. This simulator comes with the integrated 3D visual and interactive attributes of VR-Design Studio. The software allows users to create driving scenarios and re-create them with complete control of all environmental conditions, as well as being able to set individual vehicle dynamics from either within VR-Design Studio or in collaboration with such third party products like CarSim or TruckSim. The picture of driving simulator used in our experiment is given in Figure 7.

Fig-7: Fully fledged driving simulator

The simulator shown in Figure 7 supports 180º view of surrounding with its 5 independent display unit. These units are controlled by the Client PC .Moreover, the multi user client version run on each Client PC within a computer cluster is used simultaneously with the VR-Design Studio software running on the Master PC of the same computer cluster. The coordinate information of each object calculated by the Master PC is reflected on the VR-Design Studio environment within each Client PC. The multiple screens being synchronized with the Master PC, thereby allowing users on each Client PC to drive at the same time within the same environment

4.2. Customized Driving Condition by Adding Noise

In order to further enhance the realism of the simulation, we modelled the imperfections of the steering system and the effects of those imperfections on the trajectory of the car. The steering systems of real cars feature inevitable mechanical play (in steering shaft bearings, gearbox, knuckle arms, ball joints and front wheel bearings), which, together with even minor road irregularities, would result in small, random fluctuations in the steering angle of the front wheels. We modelled these oscillations by adding 2% of random value in the range $-1°+1°$ to the steering angle of the front wheels of the car at each sampling step (50 times per second) of the simulation. These random fluctuations are modelled as high frequency noise and low frequency noise added separately based on the test condition. In Fact, we considered high frequency noise as those that are generated due to variation in tires or tarmacs. We simulated high frequency noise by adding random value of 2% as mentioned previously in time interval of 20ms. Likewise, low frequency noise are those generated due to small plays in gearbox, ball joints, and knuckle arms etc., which exist due to mechanical breach between the components. Such low frequency noise were simulated by adding random noise, which remains constant until every 200ms. Furthermore, while driving in the straight section of the road both high and low frequency noise were added, whereas anticipating negligible effect of low frequency noise during turn or curving in real driving situation, only high frequency noise were added during cornering.

4.3. Evolutionary Computation

Evolutionary computation is a biologically inspired algorithmic paradigm that uses the principle of evolution in Nature, especially, the survival of fittest. As a nature-inspired algorithm, there are several terminologies borrowed from biological world, such as selection, individual, mutation, crossover and fitness. The general idea of evolutionary computation is in generating a set of individual then checking their fitness to the environment. The good ones survive to the next generation, and might have new offspring from performing genetic crossover. As the evolution repeat by itself, the fit individuals will survive, and the better genes of the individuals to fit the environment will survive.

In the terms of algorithm, the individual could represent a program or a function, determined by a set of terminals that represent genes. The environment and the fitness can represent a problem and the solution; the fit individuals to the environment means a better program or function to solve the problem towards the solution. To simulate the process of evolution and birthing new generations and offspring, a set of operators are applied to surviving individuals. There are three basic operator groups: selection, crossover, and mutation.

- **Selection**

The selection operator chooses which individuals of the population at generation, say *g*, will survive to the next generation. Common selection method is by evaluating their fitness to the environment (or problem, or target solution).

- **Crossover**

The crossover operator generates new individual (offspring) by combining the genes or parameter of two or more parent (surviving individuals). There are many ways to perform this, e.g. by swapping some parts of the genotypes of both parents.

- **Mutation**

The mutation operator is applied directly on an individual (at a gene or parameter), by performing pinpoint modifications (that can be random or regulated according to a rule). Values can be added or subtracted, or bits are flipped.

4.3.1. Genetic Programming (GP) Basic Frameworks

Genetic Programming (GP) [45] [46]is a domain-independent problem-solving algorithmic paradigm inspired by the natural evolution of species based on the survival and reproduction of the fittest. GP is successfully applied for delivering a human-competitive solutions of increasingly difficult problems in AI such as analog and digital circuits design, spatial and temporal information identification and prediction, machine learning, etc.

4.3.2. XGP Introduced

XGP [47] is an in-house GP engine that features XML (Extensible Mark-up Language) based genotype representations of candidate solutions (genetic programs), XML-schema that determines the allowed syntax of the genotypes, and a UDP channel to communicate between a fitness evaluator and the XGP. XGP manages the population of genetic programs and performs the main genetic operations – selection, crossover, and mutation.
The notoriously long execution time of GP is caused by the fact that typically, a population of many (hundreds or thousands) potential solutions to the problem (individuals) trying to find the near-optimal solution to the problem in an enormous search space. They are evolve through many (hundreds or thousands) generations based on their simulated ability (fitness) to solve the given task over many (tens or hundreds) sampled environmental situations (fitness cases). Inspired by flexibility and recently emerged widespread adoption of document object model (DOM) and extensible mark-up language (XML), XGP uses an approach of representing genetic program as a DOM-parsing tree featuring corresponding flat XML text. XGP's approach implies performing genetic operations on DOM-parsing tree using off-the shelf, platform- and language neutral DOM-parsers, and using XML-text representation as a web-compliant format, feasible for representation of genetic programs during their migration among the computational nodes in eventual distributed GP. XGP gives an advantage in the form of a faster development time due the versatility of usages: it only took a short time to change the XML-schema and adapt the desired syntax of genotypes for a program. Evolving programs using XGP requires the engine as a Microsoft Windows application running in parallel with another application to evaluate the fitness of each individual sent by XGP.

Additionally, being defined through XM-schema, XGP could be use as XGA (XML based Genetic Algorithm) framework by merely changing the schema. Unlike GP, which evolves programs/functions for a particular problem, GA, on the other hand is very useful in evolving the optimised parameters or values. Later in Chapter 7, we have employed GA in optimising the weight coefficient (*refer to Chapter 7*).

4.4. Evolving Driving Agent via XGP

Theoretically, it would be possible to verify (or discard) our hypothesis that a delay in the steering response of a driver would result in detectable steering oscillations thereby representing early warnings of a driver's inadequate cognitive load for real car(s), driven by cognitively inadequate human driver(s) in different traffic situations. Such an eventual approach, however, would be too unsafe, too slow, and too expensive.

Instead of relying on a real car, in our research, we propose the use of a simulated car in TORCS to address all of the three above-mentioned drawbacks. Our choice of a simulated (rather than a real) car heavily influenced our decision to employ a driving agent (rather than a real human) to "drive" it during our experiments, because human drivers would psychologically perceive driving a simulated car as a task that is less risky than the real one, and, consequently, would (often unconsciously) modify their driving behaviour. Therefore, we could not be completely sure about the bias in the results of the cognitive load of drivers. Along these lines, even if we had research that confirms the correlation between inadequate cognitive load and the delay in the response of a human driver, we would be unable to actually measure the actual amount of such delay in normal driving situations. Consequently, we would be unable to infer the relationship between the eventual delay and the emergent driver-induced steering oscillations (if any). With a driving agent, we could model different delays of its response and investigate the corresponding changes in its steering behaviour. In addition, allowing the driving agent to control the simulated car adds objectivity to our experiments, because we do not need to focus on actually stimulating the inadequate cognitive load (which is both subjective and individualized) in the human drivers to induce the investigated delays in their responses.

With regard to the development of such a driving agent, theoretically, it would be possible to handcraft its code (applying various top-down, theoretical approaches based on vehicle dynamics), which would model a human navigating a car on a given sample road. Such a code could be expressed as an algebraic function – a steering angle function (SAF) – of parameters, pertinent to the state of the car and the surrounding environment. However, such an approach of designing SAF might be practically unfeasible owing to the extremely complex, non-linear nature of the dynamics of real cars [48]. Indeed, it would be difficult to anticipate the mathematical relationship between the set of relevant parameters, pertinent to the state of the car, that influence the steering angle, needed to steer the car optimally in various manoeuvres (negotiating corners, changing lanes, returning to the centre of the lane following a small deviation, driving on the middle of the lane, etc.). Moreover, while a handcrafted code of SAF that involves all these parameters might definitely steer the car well on a given sample road, neither the degree of optimality of such a code, nor the method to further improve it would be apparent to a human developer. Therefore, an automated mechanism (i) to evaluate the quality of SAF, and (ii) to improve its intermediate version(s) incrementally, e.g., based on the models of natural evolution of species – might be required.

Hence, the optimal code of SAF is automatically developed via modelled evolution through selection, survival, and reproduction of the subset of the best (fittest) SAF in a way much similar to the evolution of species in Nature [45]. Such an approach involves the evaluation of the quality of many (thousands) intermediate SAF in due course of evolution, which, in turn, additionally vindicates our decision to use a simulated car as these evaluations.

4.4.1. Driving Agent; Architecture and Evolutionary Development of its Functionality

From the viewpoint of software engineering, the intended model, which simulates the steering behaviour of a human driver on a given sample road, could be considered as a (software) driving agent, that continuously perceives the state of the car and the environment. It then judges whether a steering input needs to be applied, and, if yes, acts by applying an input that turns the front wheels of the car to an appropriate – calculated via SAF – steering angle. The proposed driving agent concept is consistent with the well-established servo-control models of steering behaviour of human drivers in cognitive psychology. According to these models [49], a human driver could be viewed as an error-correcting entity, acting upon two types of perceived errors (deviations): (i) positional and (ii) heading errors.

Thus, the objective of evolving the driving agent could be rephrased as evolving the decision-making functionality of such an agent. This, in turn, implies that we would have to solve the following main tasks: When should the steering input be applied? What should the architecture of the driving agent and its decision-making mechanism be like? How much steering input to apply, i.e., what should be the contents of SAF? We discuss the proposed solutions to these tasks in the following subsections.

4.4.1.1. When to Apply the Steering Input?

The solution to this task defines the type of architecture of the driving agent: either reactive or proactive. In the latter case, the agent should be able to perceive and anticipate road conditions (direction of the approached turn, distance to the turn, its radius, etc., in the case of simple lane following) and traffic situations (number, and state of nearby cars, in case of lane changing) well ahead – both in time and space. However, such anticipation, and consequently – the corresponding anticipatory behaviour of the agent – would be too uncertain, and therefore, it would not guarantee a definite or a consistent steering response by the agent. Moreover, even if an imminent manoeuvre, say, to the right lane is foreseen, the eventual proactively-decided pattern of the applied steering angle would easily become outdated as the state of the car and, in particular, the surrounding environment (e.g., number, location, and speed of nearby cars) would be dynamic, uncertain, and non-deterministic. Hence, may require an immediate, prompt steering response.

Therefore, analogous to the servo-control model of steering behaviour of human drivers [49], we assume a purely reactive agent in that the applied steering angle is decided via SAF of the current perceptions only. The architecture of the agent is illustrated in Figure 8. We introduced a delay subsystem, as shown in Figure 8, in order to investigate the effect of cognitive load on the steering behaviour of the agent, as elaborated later in Chapter 5. In all our experiments, we consider a simple case of driving the car at a constant speed of 50 km/h, which requires trivial actions on both the accelerator and brake pedals of the car. Therefore, we excluded these actions from the decision-making functionality of the agent.

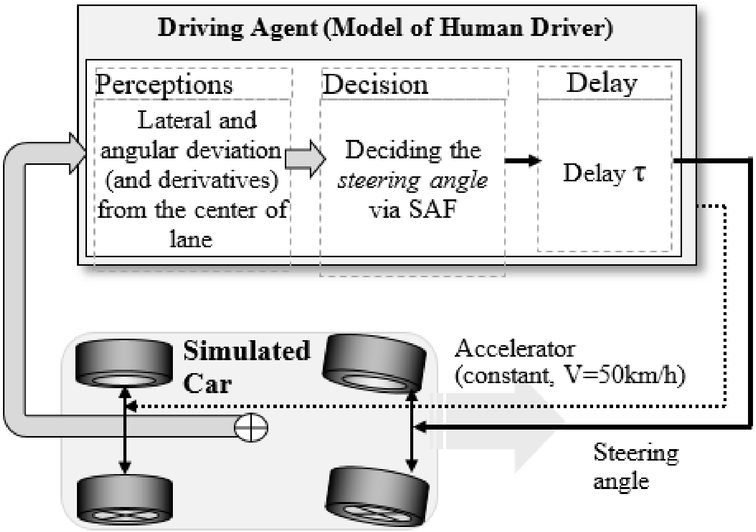

Fig-8: Reactive architecture of the driving agent: the applied steering angle is decided (via SAF) from the current perceptions only

4.4.1.2. How much Steering Input to Apply?

As previously mentioned, we are initially targeting on investigate the feasibility of applying GP to automatically develop a driving agent (as a model of a human driver) that can optimally steer a realistically simulated car with instant feedback on a varying cruising speed. Within the context of the previously introduced solutions to the task of when to apply the SAF-induced steering input, the evolutionary development of the driving agent could be considered as the evolution of an algebraic SAF (of parameters pertinent to the state of the car and their derivatives). Such SAF defines the optimal steering angle for a given steering task on a given sample road. The main features of GP, used to evolve such a function are shown in Table 2. Further, we choose the set of such terminal symbols (i.e., arguments in the evolved SAF) of GP that could provide the adopted error-correcting driving agent with sufficient information. First about positional (e.g., lateral deviation from the centre of the lane and its derivative) errors and, second about heading (angle between the centre of the lane and longitudinal axis of the car and its derivative) errors.

Table-2: Main features of GP used to evolve the optimal driving agent SAF.

Category	Value
Applied GP framework	XML-based Genetic Programming (XGP [47])
Genetic representation of evolved SAF	Dual: DOM-parse tree and XML-text. DOM-parse tree is used for the implementation of genetic operations (crossover and mutation) and for fitness evaluation. XML-text is used as a format for transmitting (via UDP channel) the SAF from the GP framework to the fitness evaluator (TORCS).
Set of non-terminals (functions)	{ +, -, *, / }
Set of terminal symbols: parameters, pertinent to the state of the car and environment, and their derivatives	{ lateral acceleration α and its derivative α', lateral deviation from the centre of the lane d and its derivative d', angle between centre line and longitudinal axis of car θ and its derivative θ'; and a random constant within the range [0..10] }
Population size	100 individuals
Selection	Binary tournament, ratio 0.1
Elitism	Best 4 individuals
Crossover	Single point, ratio 0.9
Mutation	Random subtree mutation, ratio 0.05
Fitness value	Weighted sum of (i) the area under the trajectory and (ii) the average of the lateral velocity of the car in a return-to-the-centre-of-the-line manoeuvre.
Termination criteria	(#Generations>100) *or* (no improvement of fitness for 16 consecutive generations)

We define the criterion for optimality from the desired characteristics of the driving lane during the trial of evaluating the fitness of the evolved SAFs. The trial is implemented as follows: first, the simulated car, initially positioned parallel-, 8 meters off the centre of the sample, wide straight road, accelerates slowly to 50 km/h. The speed of the car is kept constant during the trial by a simple, handcrafted feedback control mechanism that maps the difference between the desired speed (50 km/h) and the actual one into an increment (or decrement) of the position of the accelerator pedal. As the car reaches the desired speed of 50 km/h, the steering of the car assumed by the evolved SAF that instantly (without any delay) produces the desired steering angle (with a sampling interval of 20 ms) of the car's front wheels for the current values of the perception parameters. The intended, optimal, trajectory of the car, steered by the evolved SAF should be both quick and smooth and return to the centre of the lane followed by the precise drive along it (Figure 9, Case 3). We consider the trajectories shown in Figure 9 as Case 1, and Case 2 as suboptimal, as they represent either too slow (Case 1), or too quick an oscillating return (Case 3), respectively. Indeed, a too slow return would be unable to either follow adequately the centre of the lane on cornering or return to it in a case of missing it owing to the delays caused by inadequate cognitive load of the driver. On the other hand, the too quick return would imply an unnatural (for the cognitively adequate human driver), inherently oscillating trajectory of recovery. In addition, such a trajectory would be associated with both an uncomfortable (driver and passengers subjected to higher lateral accelerations) and unsafe (lateral accelerations might exceed the currently available friction of the road) drive.

To express the defined criterion of optimality of the SAF-induced steering formally, we defined the fitness function F as a weighed sum of two components. (i) The area A_T under the trajectory of the car (as an integral of the lateral deviation) and (ii) the average of the lateral velocity V_{L_AVR} (an integral of the lateral acceleration) of the car:

$$F = A_T + C \times V_{L\_AVR} \ldots (1)$$

The desired trajectory (Figure 9, Case 3) would feature an optimal trade-off between the values of these two components that result in a minimal fitness value. Indeed, the suboptimal trajectories would be subjected to a detrimental selection pressure either due to the too wide area under the trajectory (Figure 9, Case 1) or too high lateral velocity (Figure 9, Case 2).

In order to achieve a better generality of the evolved SAF, we consider two fitness cases: one with the car starting the trial right from the centre of the lane (as illustrated in Figure 9), and one - from the left. The overall fitness of the evolved SAF is calculated as an average of these two fitness cases.

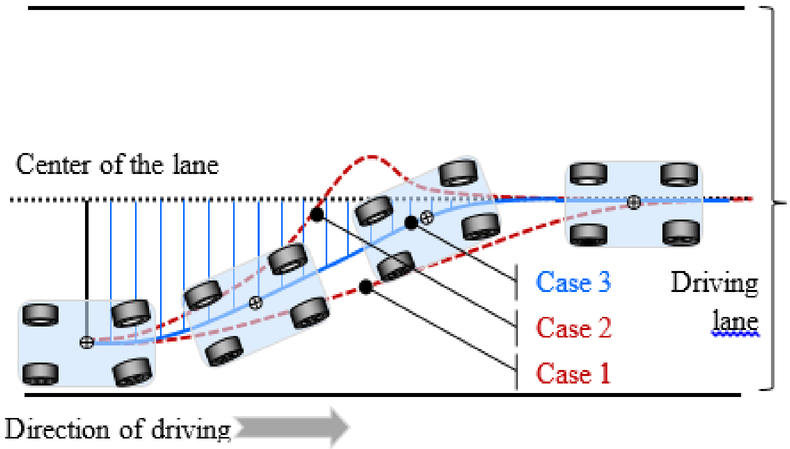

Fig-9: Trial of the evolved SAF: the intended trajectory (Case 3) of the car, steered by the evolved SAF would feature both a quick (i.e., featuring a narrow area under the trajectory) and oscillation-free (with low average lateral velocity) return to the centre of the lane. Case 1 and Case 2 illustrate a too slow and too quick (oscillating) return to the centre of the lane, respectively.

We experimentally verified that the value 0.5 of the weight coefficient C in Equation (1) results in an optimal trade-off between the values of the two additive components of the fitness function.

We would like to note that for different steering tasks, we might need to keep track of both the components of the fitness of evolved SAF separately (in a two-objective optimization approach [50]) instead of fusing both these components in a single scalar value. This would allow us to obtain a set of (Pareto-optimal) SAF that features different combinations of the area under the trajectory of the car and the average of its lateral velocity. SAF featuring a wide area under the trajectory might be needed in a slow lane change on a low-traffic highway, or in low grip (snowy, icy) road conditions. On the other hand, an SAF that results in oscillating trajectories with higher lateral speeds might be needed in circumnavigating suddenly appearing obstacles. However, for the given task of returning to the centre of the lane in normal driving conditions, the proposed simplified evaluation of the fitness of evolved SAF is sufficient

4.4.2. Evolved SAF of Driving Agent; Experimental Results

Fitness convergence characteristics of 20 independent runs of GP are shown in Figure 10. The fitness of the best-evolved SAF converges to 213 in about 40 generations of GP.

$$\text{SAF} = \frac{\alpha(8-y)}{5(8+d\prime)} - \frac{3\alpha+2d+2d\prime}{16} \quad \dots (2)$$

Where, α is the angle between the centreline and longitudinal axis of the car, y is the lateral acceleration and, d and d’ are the deviation from the centreline and its derivative, respectively.

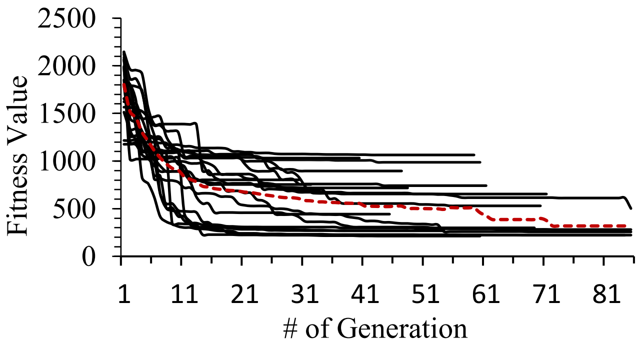

Fig-10: Fitness convergence of 20 independent runs of XGP. The dashed line represents the average of these runs.

It is common that the solutions, obtained via GP are considerably complex for humans to interpret [45]. These solutions often lack the logic that a human engineer usually applies in the usual top-down design. The presented best evolved SAF is not an exception to this phenomenon – we are unable to explain precisely either why or how this SAF works. We could only confirm, however, that the evolved SAF implements a variant of proportional-derivative (PD) control of steering in that both (i) the direct values of parameters pertinent to the state of the car and the environment and (ii) their derivatives are incorporated in its code.

The dynamics of the steering angle, the resulting trajectory (deviation from the centreline) and lateral acceleration of the car, steered by the best-of-generation SAF during the initial, intermediate, and final stages of evolution are shown in Figures 11, respectively. The best-of-run evolved SAF is shown in Figure 11d.

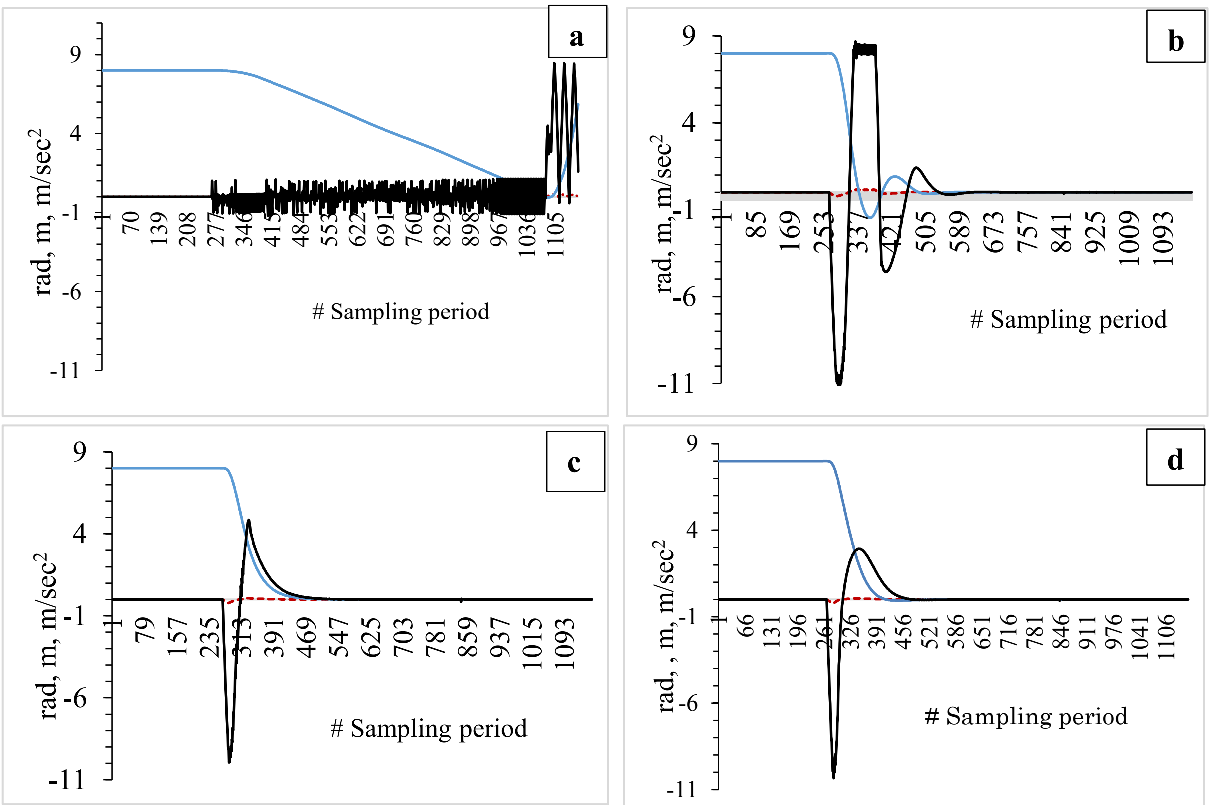

Fig-11: The dynamics of the steering angle, the resulting trajectory (deviation from the centreline), and lateral acceleration of the car, steered by the best-of-generation SAF at the initial stages of evolution. Generation #3, Fitness = 1314 **(a)**, Generation #12, Fitness = 399 **(b)**, Generation #30, Fitness = 222 **(c)**, and Generation # 42, Fitness = 213 **(d)**. The sampling interval is 20 ms.

The results shown in Figure 11d indicate that the best evolved SAF of the non-latent (with zero delay) driving agent, automatically developed via GP, offers good steering in that it exhibits a relatively quick (within 115 sampling periods – from sampling period #275 to #390) yet oscillation-free return to the middle of the lane. Moreover, the return is followed by a precise drive in the middle of the lane (from sampling periods #390 to #1132). The maximum value of the lateral acceleration (at about sampling period #275) is also moderate – less than 10 m/s^2 (about 1g).

4.5. Discussion

We intend to verify our hypothesis using different tools and technology. Initially we plan to develop a driving agent that mimics human like steering behaviour. Using GP we develop automatically, a driving agent—as a model of a human driver—that optimally steers a realistically simulated car with non-latent steering response. This driving agent mimics the human like evolutionary development process. The main reason for us to initially test our hypothesis with driving agent is because, with real human we would be unable to measure the amount of delay of response in normal driving situations, consequently, relationship between delay of response and its effect (steering oscillations) would be unclear. For example, it would be impossible to see the effect of 400ms delay and 800ms delay in human driver as response time is somehow a personal trait.

However, the result and effect of delay of response in both driving agent and human driver has been discussed in detail in the next chapter.

Chapter - 5

Hypothesis Verified; Steering Oscillation as the Effects of Delayed Response of the Driver

This chapter deals with different experiments to verify our hypothesis that delayed response of the driver due to cognitive load results in steering oscillation. First experiment is performed with the driving agent evolved via genetic programming while the other is performed with real human driver. The section 5.1 discusses the experiment with driving agent while section 5.2 deals with the experiment with human drivers.

5.1. Experiment with Driving Agent

We employed driving agent whose steering function was designed using a machine learning approach (GP). The foremost reason to employ driving agent for the initial verification of our hypothesis is because with real human driver, it would be impossible to establish the relationship between delay of response and steering oscillation The details of this agent is discussed in the following 5.1.1 subsection of this chapter.

5.1.1. Introducing Delay in Driving Agent

In this section, we present the experimental results of the characteristic changes in the steering behaviour of the driving agent when various delays of its response are introduced. The agent (steering behaviour evolved via GP), is set to drive the car at a constant speed of 50 km/h in the middle of a sample test track. The delays were set to 100 ms, 200 ms, and 400 ms for different trial. It was set separately in one of the three parts of the track according to the given three tests cases (Figure 5): (i) in the straight section of the track (Case #1), (ii) on the entry of the corner (Case #2) and, (iii) on the exit of the same corner (Case #3). In all of these three test cases, the delay is introduced briefly for a period of 2 s. Such an experimental setup represents "normal" driving conditions in that no emergent reaction (e.g., braking or steering) of the driving agent is required. The period of the introduced delay reflects our intention to model the delay that is caused by typical – brief, transient – inadequacy of the cognitive load of the driver. In addition, the chosen duration of 2 s is comparable to the typical duration of extreme – and most dangerous case – of cognitive underload – micro sleep. The typical duration of the latter is between 0.5 s and 1.5 s. As mentioned in section 4.2, in an attempt to bridge the inevitable reality gap that stems from the use of simulated, rather than real cars and drivers, we modified the source code of TORCS. This modification allows us to model of two types of steering noise: (i) high frequency noise and (ii) low frequency noise. A high frequency (50 Hz) random noise of 2% of steering angle within the range (-1°, +1°), caused by road irregularities (micro-bumps) and vibrations of the rolling tires. These cause instant variations of the rolling radii of all four wheels of the car that, in turn, would result in a noisy steering of the car. In addition, on the straight section of the road we model lower frequency (10 Hz) variations of the steering angle, by adding random noise of 2% as mentioned above. The low frequency noise are caused by plays (and the resulting hysteresis) that normally exist in the joints linking the components (steering shaft, gearbox, tie rods, knuckle arms, kingpins, etc.) of the steering system of the road cars [51]. However, no low-frequency noise is assumed when cornering, as these plays are bridged by the centripetal forces applied to the steering components of the car.

5.1.2. Effects of the Delay of Agent's Response on its Steering Behaviour

The experimental results of the effect of delay of 100 ms, 200 ms, and 400 ms of steering response, introduced for 2 s on the straight section of the road (test case #1) are shown in Figure 12. As Figure 12 indicates, the delay in steering response causes a small (and independent of the amount of delay) – yet detectable from noise – oscillation in both the steering angle and lateral acceleration. In the second and third test cases (Figure 13 and Figure 14), the delay of steering response, introduced at the entry and exit of the turn causes significant steering oscillations with an amplitude that increases with an increase in the amount of the introduced delay. These oscillations are well distinguished from noise by both the different main frequency (about 0.5 Hz, much lower than those of the steering noise) and amplitude.

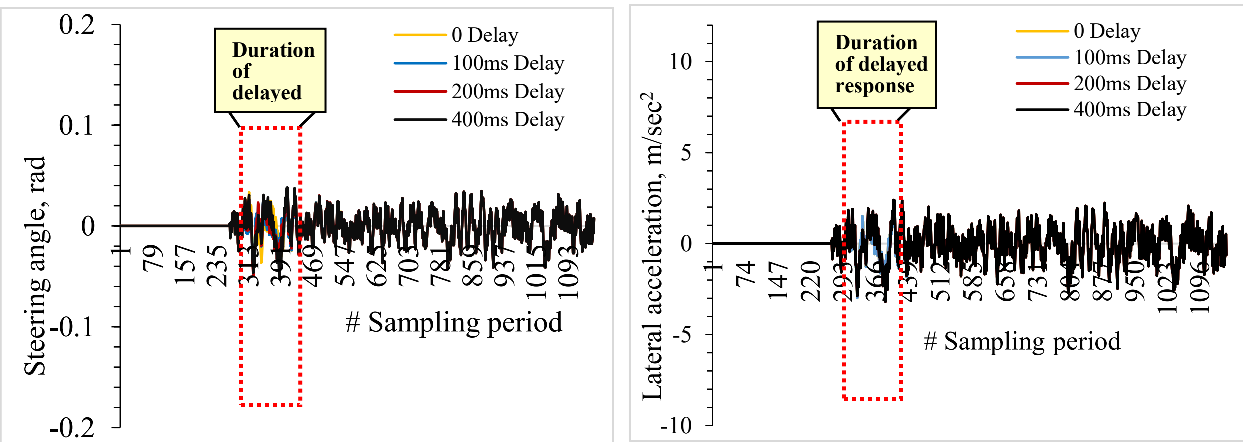

Fig-12: Dynamics of steering angle (left) and lateral acceleration (right) when a steering response delay of 100 ms, 200 ms, and 400 ms is introduced for a duration of 2 s on the straight section of the road (test case #1). The sampling interval is 20ms

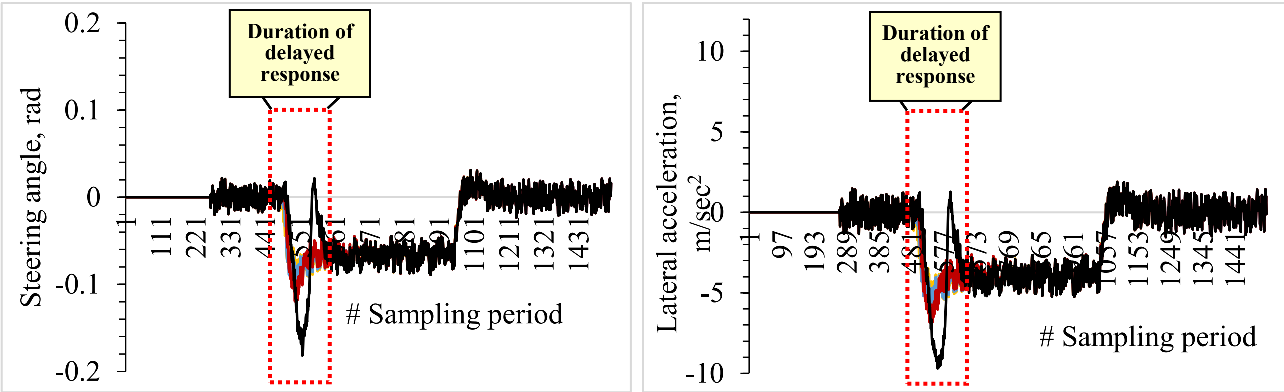

Fig-13: Dynamics of steering angle (left) and lateral acceleration (right) when a steering response delay of 100 ms, 200 ms, and 400 ms is introduced for a duration of 2 s on the entry of the turn (test case #2). The sampling interval is 20ms.

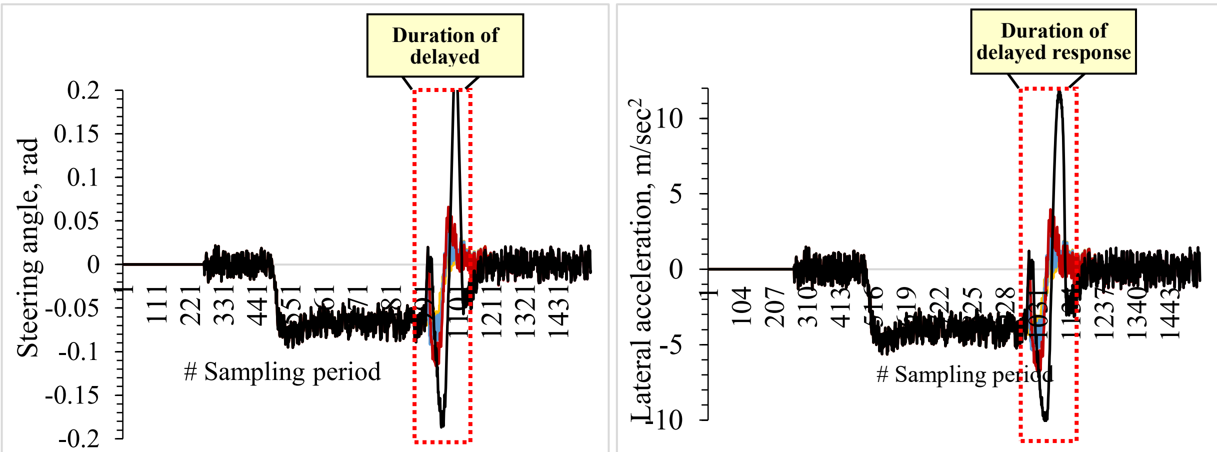

Fig-14: Dynamics of steering angle (left) and lateral acceleration (right) when a steering response delay of 100 ms, 200 ms, and 400 ms is introduced for a duration of 2s on the exit of the turn (test case #3). The sampling interval is 20ms.

5.1.3. Effect of Change in Speed and Agent's Response on its Steering Behaviour

This section presents the results on the steering behaviour due to delay in response of the driving agent while driving at a different (yet constant) speed. Initially, we experimented with a cruising speed of 50 km/h. *The corresponding results (Figure 12, Figure 13, and Figure 14) show that well-distinguishable steering oscillations are induced as a result of delay in response (due to inadequate cognitive load) of the driver*.

To further measure the robustness of the evolved driving agent and to observe the effect of change in speed in the steering behaviour of the driving agent (due to cognitive delay), we further experimented with the driving agent for different cruising speeds. However, the delay in response was set constant to 400 ms for all additional cases. Table 3 shows the experimented cruising speeds of the car.

Table-3: Experimented cruising speeds of the car

Speed (km/h)	Delay (ms)
40	400
60	400
70	400
80	400

We tested the agent for varying (yet constant for each of the experimental cases) cruise speeds of 40 km/h, 60 km/h, 70 km/h, and 80 km/h, (note that 50 km/h was initially tested as mentioned in Section 4 of this paper). Delay in the steering response is set to 400 ms and the experiment was performed for three different driving conditions. The dynamics of the lateral acceleration for each of these cases while driving on the straight section, driving on the entry of corner, and on exit of a corner, with a delay in steering response are shown in Figure 15a, Figure 15b and Figure 15c respectively.

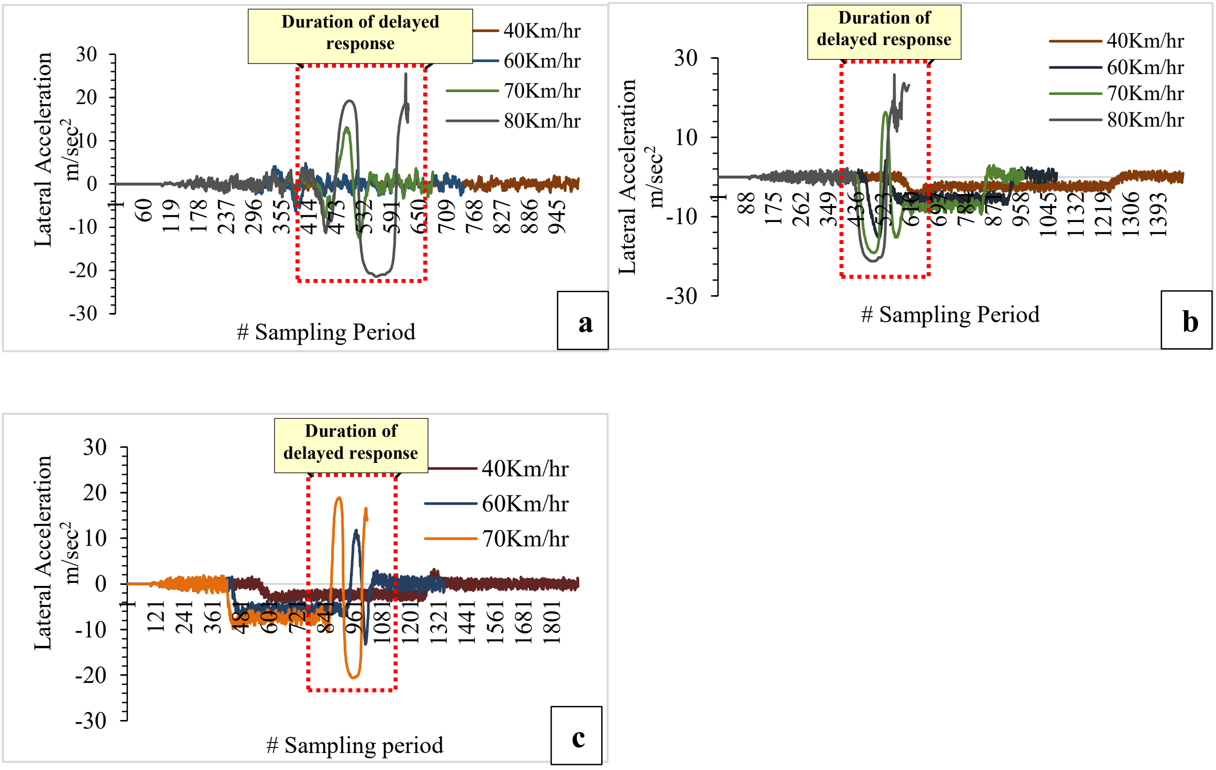

Fig-15: Dynamics of lateral acceleration when a steering response delay of 400 ms is introduced for a duration of 2 s on (a) the straight section of the road, (b) the entry of the road, and (c) the exit of corner. The cruising speeds are set to 40 km/h, 60 km/h, 70 km/h, and 80 km/h, respectively. The sampling interval is 20ms.

The experimental results shown in Figure 15 demonstrate that the evolved model of driving agent with non-latent steering response could well adapt to the different cruising speeds of the car in different driving conditions, such as driving on straight and corner sections of the road. In addition, it illustrates the effect of various speeds on the steering oscillations of a vehicle driven by cognitively delayed agent. The experiments on the straight section and curve entry section (Figure 15a and, 15b and 15c respectively) show that oscillation increases in terms of both amplitude and wavelength with the speed. In addition, the driving agent has not been able to control the effect of 400 ms delay continued for 2 s in the case of 80 km/h speed while the same lack of control could be observed for 70 km/h in curve exit case (Figure 15c). This however, highlights the fact that, the oscillation could be more severe in the exit of the corner even with limited speed of a vehicle combined with inadequate cognitive engagement of the driver although the effect in the other two conditions is also very significant.

5.1.4. Discussion

We verified the hypothesis that a simulated delay in the steering response of the evolved model of a human driver results in well-expressed steering oscillations. The experimental results of the impact of speed on a computationally evolved driving agent highlight the robust nature of our approach. Further, it has also been observed that increase in speed increases the amplitude of the oscillation, thus underlining the extreme consequences of driving with inadequate cognitive engagement.

The detection of these oscillations could assist in providing early warnings of inadequate driver cognitive load in normal driving conditions – and well before an urgent response to an imminent hazardous traffic situation is required. However, similar effect has to be observe in real human driver to understand and outline methodologies for oscillation detection. The following experimental has been done to observe the similar effect of oscillation in real human drivers.

5.2. Experiment with Human Drivers

The verification of our hypothesis with the evolved model of a human driver naturally motivated us to experiment with human drivers. Therefore, we made another experiments with real human drivers, which is discussed in following subsection 5.2.1.

5.2.1. Introducing Delay via Distraction in Human Drivers Cognition

Theoretically, we have seen from the Chapter 2 that any inattention including distraction induce inadequate cognitive load in driver and as a result, such cognitive load would result in delay of response or higher response time. Therefore, we try to observe the effect of cognitive overload in real driver in two separate conditions; (i) by introducing cell phone texting while driving and, (ii) by artificially introducing delay in the steering control of the car (details in Subsection 5.2.2). We anticipate that there will be the similar effect in both of this case. Further, texting while driving is extensively studied, and it is recognized as both (i) an effective and (ii) most often seen form of driver distraction [35] [52]. Hence, we conducted our experiments on texting while driving in order to provoke the naturally occurring DoR in the human driver.

5.2.2. Additional Experimental Conditions

In order to verify whether the cognitive load in human drivers would produce similar patterns of steering behaviour, we conducted two groups of experiments: first we introduced the delay of 400ms (comparable to the typically documented amount of delay caused by cognitive inattention) artificially in the steering system of the car. Then we induced a cognitive distraction by requesting 10 human drivers either to text or to conduct a hands-free phone conversation while driving. In both cases we experimented with 10 different human drivers. The experimental conditions are summarized in Table 4.

Table-4: Experimental conditions

Conditions	Artificially introduced delay of 400 ms in the steering system of the car	Cognitive distraction while driving, that might result in DoR
		Texting while driving
Test case	Straight	Straight
	Corner Entry	Corner Entry
	Corner Exit	Corner Exit

The age of the human drivers was between 23 to 35, and the ratio of female to male drivers was 4:6. From 10 drivers. For a better consistence of the results, we conducted the experiments with each of the drivers in two consecutive days. In the first day, each driver was provided with sufficient time to become familiar with the system and the simulated driving environment in TORCS (with steering wheel and pedal additionally connected to the system) in normal condition without any cognitive distractions or artificially introduced steering delays (learning phase).

Consonant with the recognition that sleep is vital for the learning by contributing for the consolidation of memory [53] [54], in order to allow the drivers to learn well how to drive the simulated car, we conducted the actual experiment on the following day. Subjects were required to drive in simulator in two experimental conditions: first with artificially introduced delay of 400ms in the steering system of the car, and then – with cognitive distraction (that, ultimately, might result in DoR) induced by either texting or hands-free conversation while driving. In all the experimental cases, a constant speed of 50km/h was maintained by simulated cruise control system of the car.

5.2.3. Effect of the Delay of Driver's Response on Steering Behaviours

The experimental results on the effect of artificial delay and cognitively distracted sample driver on the dynamics of lateral acceleration of the car for the three test cases (straight, corner entry, and corner exit) are shown in Figures 16, Figure 17, and Figure 18, respectively. As these figures illustrate the cognitive distraction and artificially introduced delays result in similar oscillating patterns of lateral oscillations. These oscillations could be distinguished well from the noise occurring from the modelled (i) plays in the joint of steering system, and (ii) small irregularities of the road. As the results shown in Figures 16, Figure 17, and Figure 18 indicate, for the majority of the drivers the introduction of either a cognitive distraction or artificial delay in the steering system of the car result in increasing of the amplitude of oscillations of lateral acceleration of the car in all three considered test cases.

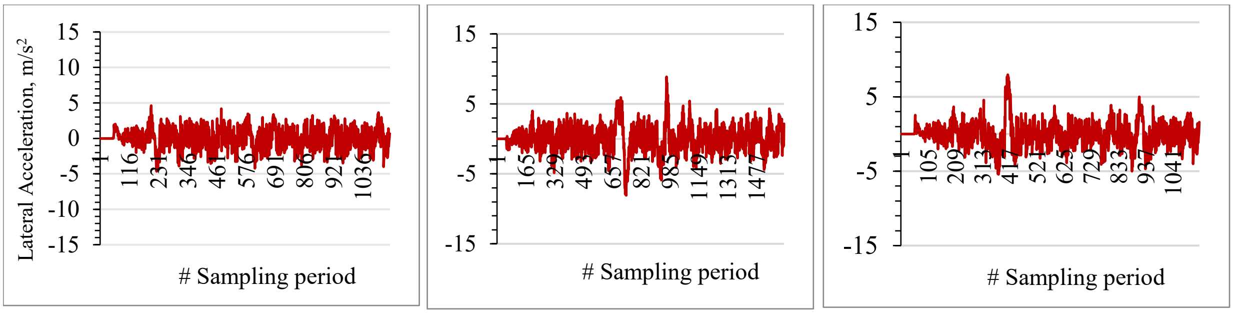

Fig-16: Dynamics of lateral acceleration of the car when driven by sample driver in normal condition without delay or cognitive distraction (left), with cognitive distraction (naturally-induced DoR) caused by texting while driving (middle) and artificial delay of 400ms introduced for duration of 2s in the steering system of the car (right) on the *straight section* of the road (test case #1). The sampling interval in all three cases is 20ms.

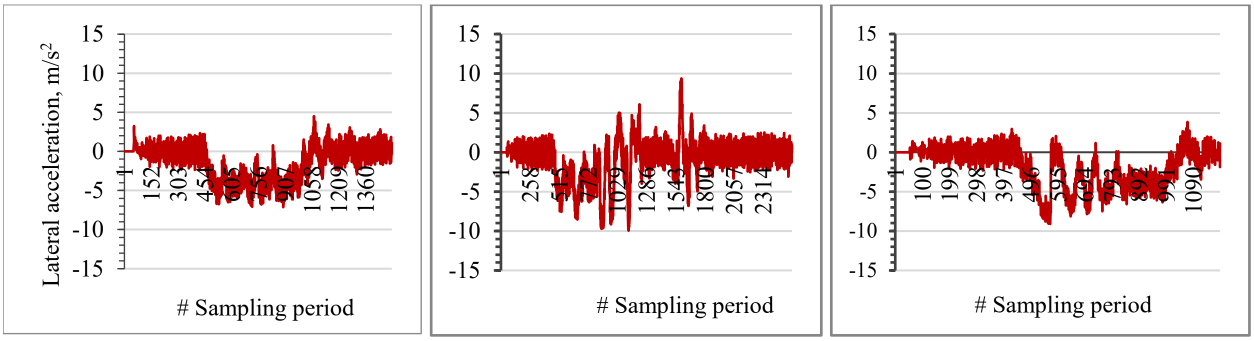

Fig-17: Dynamics of lateral acceleration of the car when driven by sample driver in normal condition without delay or cognitive distraction (left), with cognitive distraction (naturally-induced DoR) caused by texting while driving (middle) and artificial delay of 400ms introduced for duration of 2s in the steering system of the car (right) on the *entry of the corner* (test case #2). The sampling interval in all three cases is 20ms.

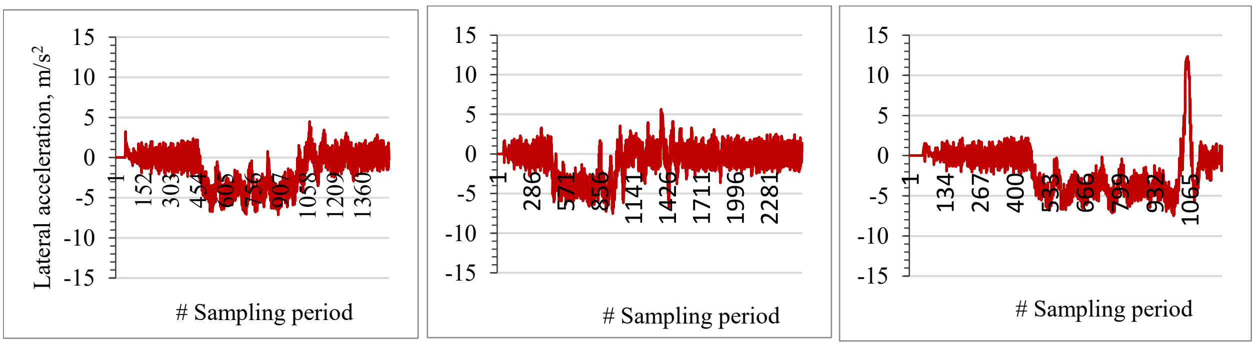

Fig-18: Dynamic of lateral acceleration of the car when driven by sample driver in normal condition without delay or cognitive distraction (left), with cognitively distraction (naturally-induced DoR) caused by texting while driving (middle) and artificial delay of 400ms introduced for duration of 2s in the steering system of the car (right) on the *exit of the corner* (test case #3). The sampling interval in all three cases is 20ms.

5.2.4. Discussion

The result shows that a simulated delay in steering response of the evolved model of human driver result in well expressed steering oscillations. In addition, the experiment conducted with real human driver verifies same effect of steering oscillation. The additional experimental results on the impact of speed on a computationally evolved driving agent highlight the robust nature of our approach on verifying the forwarded hypothesis. Further, it has also been observed that increase in speed increases the amplitude of the oscillation, thus underlining the extreme consequences of driving with inadequate cognitive engagement.

The detection of these oscillations could assist in providing early warnings of inadequate driver cognitive load in normal driving conditions – and well before an urgent response to an imminent hazardous traffic situation is required. We can observe from the experimental result that the wavelength of driver-induced steering oscillations is (i) shorter than that of normal cornering, but (ii) longer than that of the noise; therefore, we believed that a reliable detection of these oscillations could be achieved by real-time spectral analysis of the signal of lateral acceleration of the car. Thus, Chapter 6 provides the details on the approach of detecting steering oscillation using spectral analysis.

Chapter - 6

Proposed Method for Oscillation Detection

6.1. Oscillation Detection using Spectral Analysis

With the successful verification of our hypothesis that, cognitive delay in human driver result in steering oscillation, we next aimed for its detection so that accidents that occurs due to inattention and/or distraction could be prevented. Therefore, one of the very basic approach of detecting steering oscillation of a driver (resulting from a cognitive load) would be through the measurement of power spectrum (Spectral density) of the oscillated signal. Hence, we implemented (i) Fourier transformation to transform the time domain signal into the frequency domain and then (ii) calculated its power spectrum. We considered that, the magnitude of signal oscillated due of cognitive delay would be higher than the normal signal, and thus the power spectrum would be different, that would allow us to distinguish the oscillated and non-oscillated signals. The block diagram of the model is shown in Figure 19.

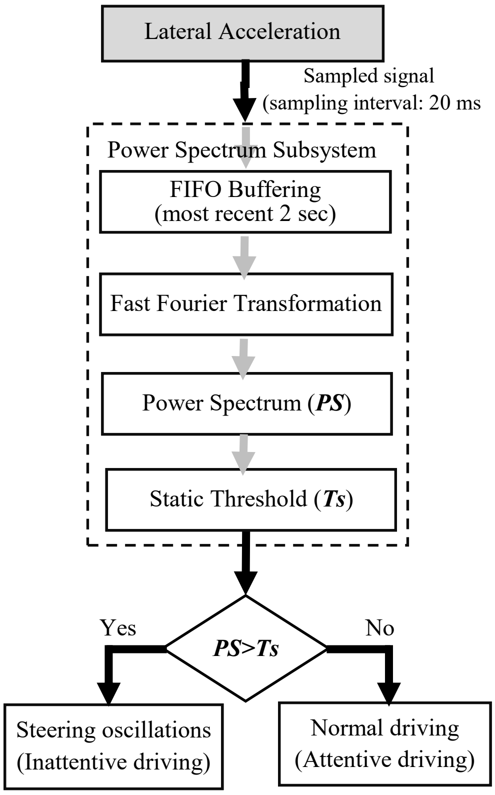

Fig-19: Block diagram of proposed detection methodology using static threshold

The block diagram shown in Figure 19 illustrated the proposed approach for oscillation detection based on static threshold. As shown in the model, first the lateral acceleration signals of the car are accumulated in a FIFO buffer. Second, Fourier transformation is applied to the signal. Finally, power spectrum (PS) value of the transformed signal are calculated. Once based on the maximum PS value of the normal driving condition, the static threshold is setup. This method then compares the value of PS with the static threshold and identify if the signal was steering oscillation induced due to inattentive driving or the normal driving. The model/methodology for the oscillation detection is further describe in following sub-section.

6.1.1. Methodology of Oscillation Detection

The proposed approach features three phases: first, we collected the raw signal – time series of lateral acceleration of a simulated car, driven by human driving in the following two situations: (i) inattentive driving (driving while texting) and (ii) attentive driving (normal driving). In the second phase, we apply Fourier transformation on the time series of lateral acceleration in order to obtain its spectrum. Finally, in the third phase, we calculate the power spectrum (PS) of the transformed signal, which has been divided in two stages as (i) acquisition of later acceleration time series and (ii) analysis of power spectrum signal of lateral acceleration, and are further elaborated below.

6.1.1.1 Acquisition of lateral acceleration time series

- **The Apparatus and its Parameters**

As mentioned previously, we adopted an approach for acquiring and analysing the signal of the lateral acceleration of the car by modelling in the TORCS environment. The various merits and demerits of using TORCS environment is discussed in Section 4.1 of Chapter 4. In a real-world scenario, the instant values of the time series of lateral acceleration could be easily obtained from a low-cost, non-invasive sensor, such as accelerometer. Moreover, many modern vehicles are already equipped with such a sensor. The sensor is used to provide information about the current state of the car to the electronic stability program and the GPS-based navigation system (used for dead reckoning when GPS signal could not be obtained).

We consider our current work on simulated car just as a first – yet an efficient, inexpensive, and safe – step towards the verification of our concept. As a next step, we are planning to replicate the experiments in real cars driven in real-world situations.

- **The Drivers and the Experimental Procedure**

We requested 10 human drivers to drive the above-specified simulated car using realistic controls (i.e., steering wheel, accelerator, brake pedals) all between the age group of early 20's to early 30's. In order to acquire the signal for oscillating lateral acceleration, we intentionally distracted the drivers at arbitrary sections of a long road (featuring straightaways and corners) by asking them to read, comprehend, and respond to text messages that were sent to their mobile phones while driving. We adopted texting as the cause of distraction, because it is extensively studied case and a major cause of distracted driving. The oscillating lateral acceleration of the moving car would be a natural consequence of the delayed steering response, which is caused by the inadequate cognitive load of the driver, e.g., due to the experience of above-mentioned distractions during driving.

In addition, in order to guarantee that the cognitive engagement of the drivers is shared only between steering (primary task) and texting (secondary task), we freed the drivers from any unnecessary cognitive burden that would have been required to maintain the desired speed of the car. In other words, we implemented a simulated cruise control function that automatically accelerates the car to 51 km/h (14 m/s) and maintains this speed through the entire experiment.

Considering the findings of neuroscientists, which describe that sleep facilitates the consolidation of memory and is therefore crucial for the learning of new abilities, we performed the experiments over the course of two days. On the first day, we allowed the drivers to familiarize themselves with the software system, the simulated car, and its controls, and we conducted the experiments involving actual driving the following day.

- **Workload Parameters**

As previously mentioned, we measured the steering angle, deviation from the centreline, and the lateral acceleration of a vehicle when being driven by the driver with both (i) attentive driving and (ii) inattentive driving condition. All these were acquired as time series. However, we only analyse the signal of lateral acceleration of the car for the detection of steering oscillation. The procedure of analysing the lateral acceleration is elaborated in the following subsection.

6.1.1.2. Analysis of the PS of Lateral Acceleration

The verification of the assumption that inadequate cognitive load in drivers results in steering oscillations motivated our quest for a reliable method to detect these oscillations. Therefore, we consider the method of analysing the magnitude of the PS of the Fourier-transformed signal of the lateral acceleration of the car, anticipating that such a method might allow us to segregate the frequencies pertinent to driver-induced oscillations from noise frequencies, and not from the frequencies of normal steering of the car around corners. Thus, we first perform a Fourier transformation on the acquired time series of the lateral acceleration of the car. The transformation was conducted in offline mode, and it does not require any additional driving experiments with human drivers. However, in order to model a real-time implementation of the proposed approach, we initiate the transformation with an initial window of 100 samples (corresponding to the first 2 s of data). Then, we calculated the value of the PS in the frequency range of the obtained spectra of the initial 2 s, 1–50 Hz, and associated this PS value with time tinitial+2s. Next, we proceeded by repeatedly sliding the 100-sample window by one frame (corresponding to the sampling interval of 20 ms) and performed the Fourier transformation and the PS calculation until we reached the final 100 samples of the acquired time series. The Fourier transformation and PS from the Fourier-transformed signal of lateral acceleration is calculated as follows:

$$X(k) = \sum_{n=0}^{N-1} x(n) \times e^{-i\frac{2\pi nk}{N}} \ldots (3)$$

Where, k is used to denote the frequency domain ordinal, n is used to represent the time-domain ordinal, N is the length of the sequence to be transformed.

$$PS_{1\sim 50} = \sum_{i=1}^{50} (A_i)^2 \ldots (4)$$

Where, $PS_{1\sim 50}$ is the power spectrum in a frequency range between 1–50 Hz, and A_i is the amplitude of frequency i, in the spectrum of the Fourier-transformed signal. *Note that, power spectrum of signal is calculated every t time interval rather than that of whole dataset. Therefore PS = PS_t, where t is the time interval. Computationally it is made possible by maintaining fixed sized FIFO buffer (dataset of 2 s) and sliding them with one frame as mention previously.*

6.1.2. Experimental Result

For each of1the two driving conditions, we consider two cases of cognitive load as mentioned in previous sections: (i) normal load when the driver could focus completely on driving (attentive driving) and, (ii) cognitive overload caused by texting on mobile phone while driving (inattentive driving). In the second case, we requested each of these drivers to respond to a text message (that was sent to the messaging application running on their mobile phone) while driving. The texting was intended to induce inadequate cognitive engagement and the corresponding DoR in their primary task of driving. We registered the raw signal (with sampling interval of 20ms) of the lateral oscillation of the car driven by all subjects in all driving conditions. Then we used the raw data to perform an offline analysis of the power spectra for all 10 cases. Figures 20a and 20b illustrate the typical forms of the raw signal of lateral acceleration of both attentive and inattentive driving on straight (Figure 20a) and curve (Figure 20b) of the road, respectively. The corresponding values of the PS are illustrated in Figures 21a and 21b.

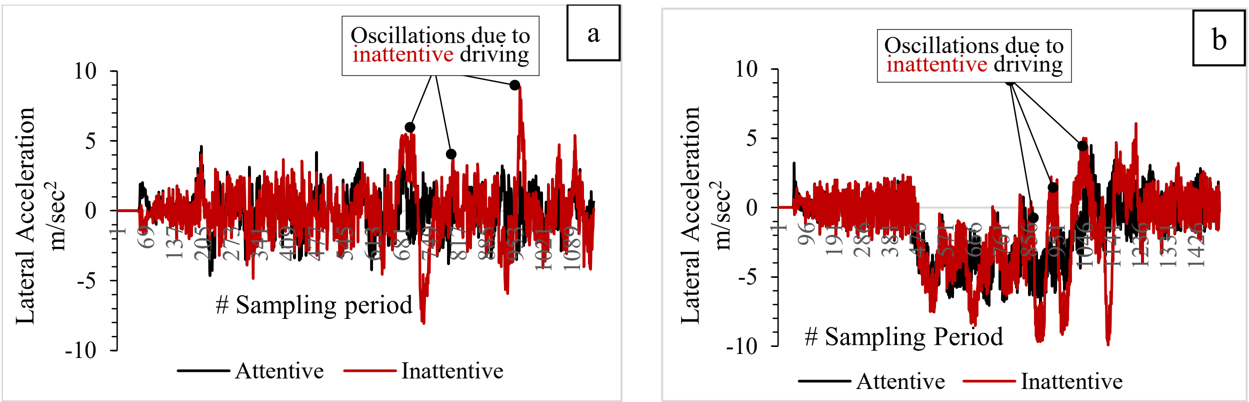

Fig-20: Typical dynamics of lateral acceleration on straight (a) and curve (b) section of the road.

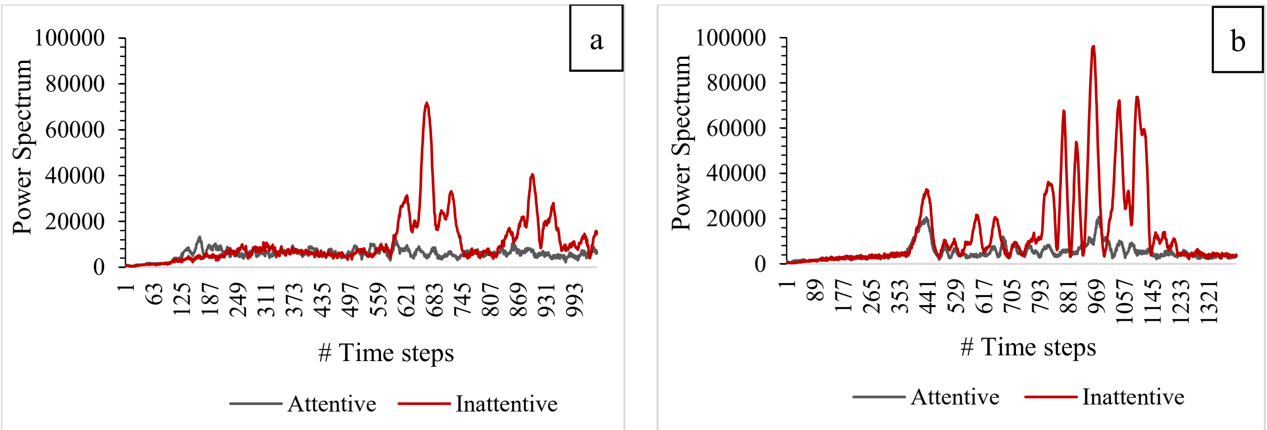

Fig-21: Typical dynamics of PS on straight (a) and curve (b) section of the road.

As Figures 20a and 20b illustrate, the lateral acceleration for inattentive driving (and resulting DoR) due to texting while driving in both driving conditions (i.e. driving on a straight and on cornering) feature subtle, yet distinguishable oscillations. No such oscillations could be observed in the case of normal (attentive) driving. The corresponding PS of the lateral acceleration of inattentive driving is higher than that of attentive driving (Figures 21a and 21b).

6.1.3. Classifying Inattentive (oscillating) and Attentive (non-oscillating) Case

The above approach was implement to get maximum value of PS of lateral acceleration during attentive and inattentive driving of all 10 drivers on straight and corner section of the road, respectively, which is illustrated in Figure 22. As shown in the figure, considering a fixed, single threshold (shown as dotted horizontal line), would result in correct recognition of oscillatory steering behaviour of the car in 80% to 90% of the drivers. These results also indicate that different drivers indeed experience different level of steering oscillation resulting in varying PS.

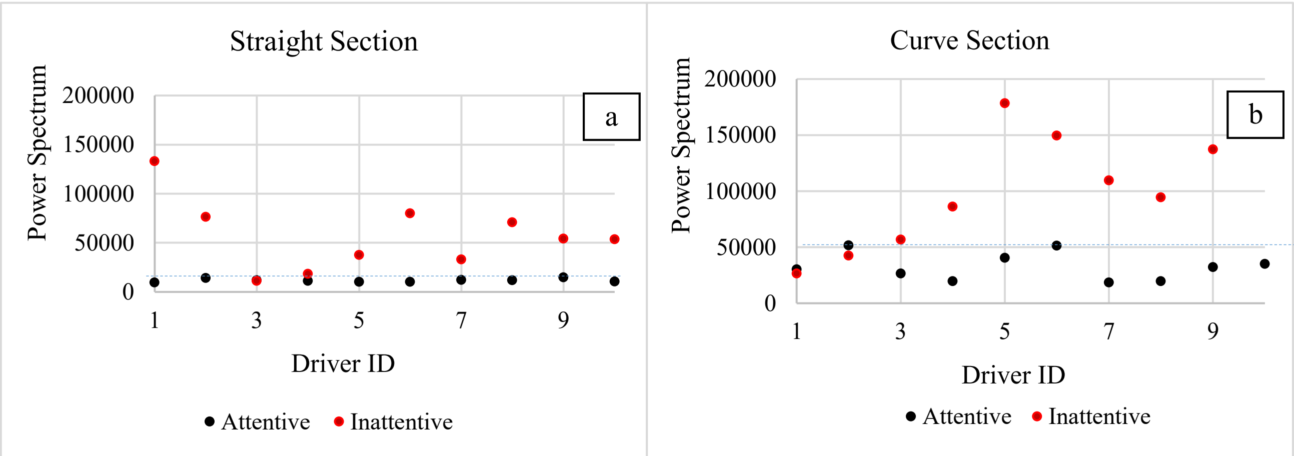

Fig-22: Maximum value of power spectrum of attentive driving and inattentive driving on straight (a) and curve (b) sections of the road

However, considering the driving as a subjective activity that depends on drivers we have to acknowledge the fact that a single average value of the threshold that could be successfully applied to all drivers might be non-existent [55]. Therefore, in the next subsection, we discuss the limitation of the approach and highlight the possible solutions.

6.1.4. Discussion

6.1.4.1. Limitation of the Proposed Methodology

Although, with this method (setting up a static threshold) we could achieve at-least 80% success on our classification task it still holds some limitation. The two very common limitation of our approach are further discussed below;

- **Variation in PS with Respect to Driving Conditions**

We hypothesize that, since both the magnitude and the corresponding frequencies of the oscillating signal would be different from those of the normal signal, the resulting value of the power spectrum would be diverse (presumably – higher) as well. Figure 23a illustrates that, for a sample driver (Driver A), the PS of inattentive driving on a straight section of the road is, indeed, higher than that of attentive driving through corners.

However, the preliminary experimental results also suggest that, due to the diversity of driving conditions (straight, corner entry, steady state cornering, and corner exit) and the driver-dependent features of the acquired signals, the PS of inattentive driving along a straight section of the road could be lower than that of attentive driving when negotiating corners. The PS in cornering could be anomalously high due to extensive (yet, non-oscillating) movements of the steering wheel when entering and exiting corners. Figure 23b illustrates that, indeed, for another driver (Driver C) the PS of inattentive driving along a straight section of the road is lower than that of attentive driving through corners.

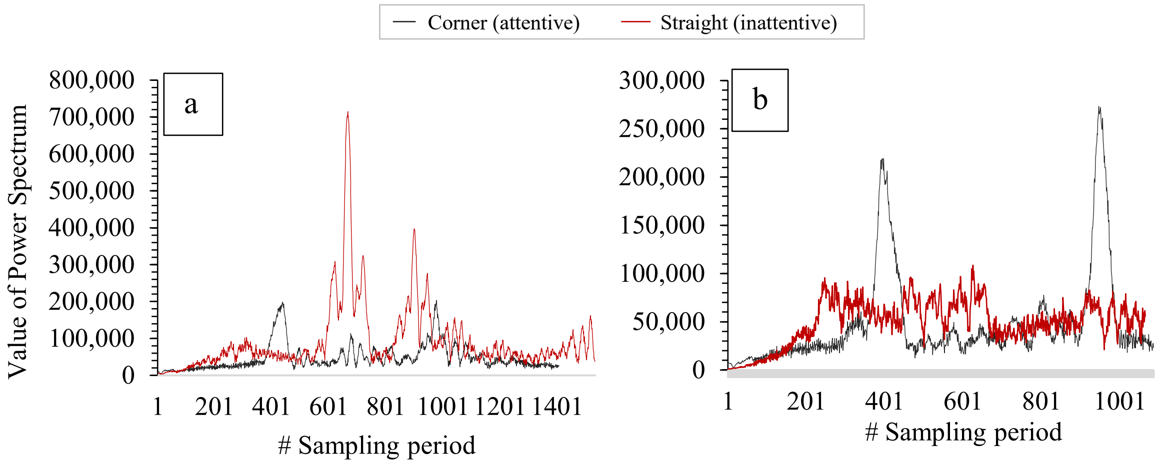

Fig-23: PS of lateral acceleration of car driven by ***(a)*** *Driver A* and ***(b)*** *Driver C*, both inattentively (on straight section of the road) and attentively (in corners).

Based on the experimental results, as shown in Figures 23a and 23b, we could conclude that it would be difficult to devise general robust method to detect the inadequate cognitive load of drivers from steering oscillations by merely comparing the values of canonically calculated PS (as shown in Equation (4) to a given threshold.

This make us necessary to find some additional approach that does not varies in spite of variable driving conditions.

- **Inexistence of Average Threshold in Human Factor**

Driving is a personal activity and it purely depends on the driver's personality and/or training and experience. Therefore, considering a single threshold for the classification would not be natural for all the cases, as it might not address all the driving cases.

Hence, some additional approach is required to address these limitations, which are discuss in the following subsection and are further elaborated on Chapter 7 and Chapter 8.

6.1.4.2. Possible Solutions

To address the limitation of the current approach, we further extended our research in two different direction. (i) Implement the Genetic Algorithm (GA) to optimize the coefficient of the PS in such a way that, it would solve the issue of variation in PS while driving in different conditions. (ii) Innovate novel approach that would adapt with individual driver. As mentioned, each of this approach are further elaborated in chapter 7 and chapter 8 respectively.

Chapter - 7

Enhancing Proposed Method via XGA

7.1. Introducing Weight Coefficient to the PS

To address the limitation of the proposed model to detect steering oscillation by comparing PS with static threshold as mentioned in 6.1.4 section of Chapter 6, we investigated whether applying different weight coefficients to the components of the sum in the equation of the PS (1) would result in improved recognition of the steering oscillations. Hence, we divided the equation of power spectrum and introduced weighted coefficient as shown in following Equation 5.

$$WPS_{1\sim 50} = w_1 \times A_1^2 \ + \ w_2 \times A_2^2 \ + \ .... \ + \ w_{50} \times A_{50}^2 \ ...(5)$$

Where, *WPS* is the weighed power spectrum in the frequency range 1Hz to 50Hz, A_i is the amplitude of the frequency iHz (i=1…50) in the spectrum of the Fourier-transformed signal, and w_i is the weight coefficient of the amplitude A_i.

The rationale behind the use of such weight coefficients is that the frequencies that are pertinent to attentive and inattentive driving might be different, and, therefore, their amplitudes should be accounted differently. Therefore, the detection of, e.g., inattentive driving could be facilitated by emphasizing the amplitudes of frequencies that are pertinent to this type of driving by means of using larger weight coefficients. The block diagram of this approach has been given in Figure 24.

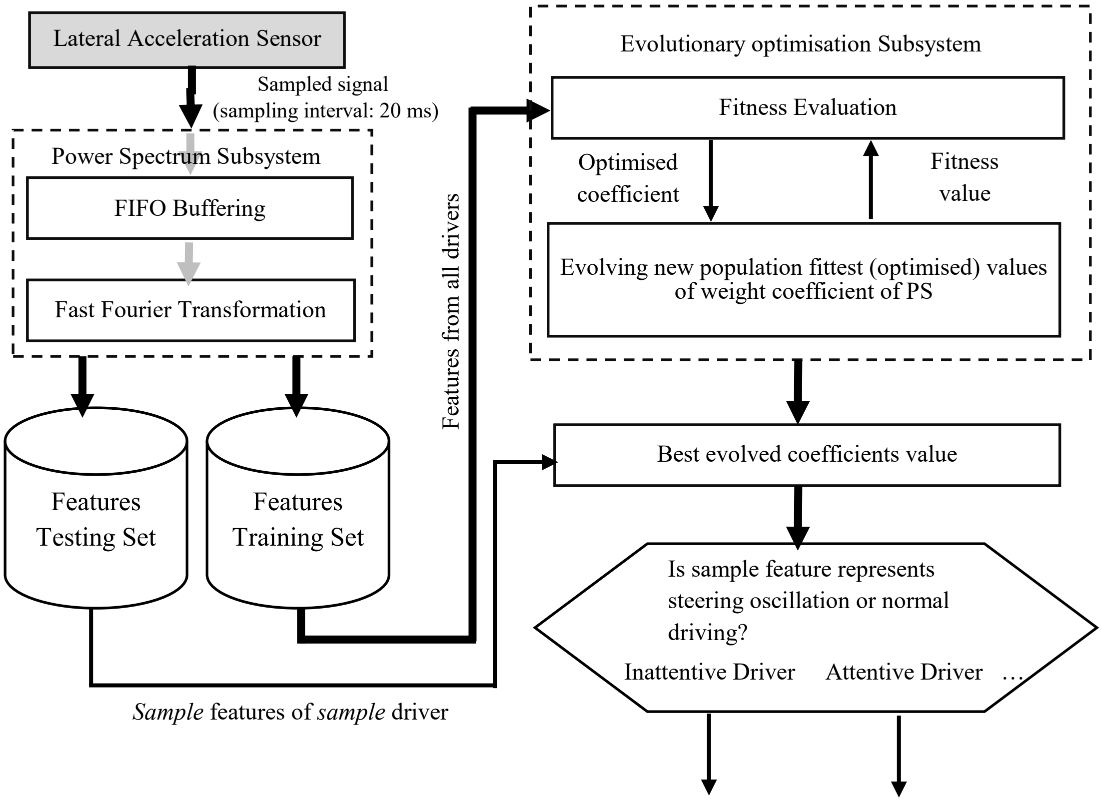

Fig-24: The block diagram showing the enhancement of GA for optimising weight coefficient of PS.

Figure 24 shows the block diagram of the model proposed for enhancing the weight coefficient of PS via GA. This diagram consist of two independent module. The Power spectrum module is similar with the previous model describe in chapter 6. However, after performing the Fourier transformation of the signal from the buffer, we generate features by diving the signals in ten different groups. The more of this is explained in Genetic Representation section of this chapter. The next module is the Evolutionary optimisation module. The module is responsible for performing genetic operation to uncover the best possible coefficients based on fitness evaluation. Once the best-evolved coefficient value is determined, these values are used as weight coefficient in PS (eq.5) to identify if the signal is normal (attentive driving) or oscillated (inattentive). The following section describe the details of this process.

7.2. Applying GA for Evolution of Optimal Values of Weight Coefficients of WPS

We decide to apply a heuristic approach to the "tuning" of the weight coefficients of WPS because we are *a priori* unaware of the exact set of frequencies in the spectrum of lateral acceleration that characterize either the attentive or inattentive driving. In principle, we could have adopted another – deterministic – approach, such as, for example – complete enumeration of the possible combinations of weight coefficients. However, because we consider *50* frequencies (*1Hz, 2Hz, 3Hz,…* , *50Hz*) in PS, represented by their respective amplitudes $A_1, A_2, A_3, \ldots A_{50}$, we would need to search for the optimal combination(s) of the values of *50* weight coefficients $w_1, w_2, w_3, \ldots w_{50}$. Assuming that each of these weight coefficients is discretized into, say, just *100* possible values, the size of the resulting search space would be 100^{50} (or, 10^{100}), rendering the eventual "brute force" approaches, based on complete enumeration of possible combinations of values of weight coefficients computationally unfeasible.

GA, on the other hand, is a nature-inspired heuristic approach that gradually evolves the optimal values of set of parameters in a way much similar to the evolution of species in nature. GA is proven efficient for finding optimal solution(s) to combinatorial optimization problems featuring large search spaces [56] [57]. Thus, we adopted GA to evolve the optimal values of the weight coefficients of WPS. The optimality implies that the WPS of the signal of lateral acceleration of the car would allow for the best possible discrimination between the attentive- (non-oscillatory) and inattentive driving (with steering oscillations, caused by inadequate cognitive load). The main features of the adopted GA – genetic representation, genetic operations and fitness function are elaborated in the following subsection.

7.2.1. Genetic Representation:

The simulated individuals in GA are represented by their respective chromosomes. The latter consist of an array of the real values of the evolved coefficients of WPS. The vales of the weight coefficients, are constrained within the range *[0…9]*, and are divided into *90* possible discreet values. Such a chromosome, containing an array of all *50* weight coefficients $w_1, w_2, w_3, \ldots w_{50}$, however, would result in the size of 90^{50} of the search space, that would have been computationally intractable not just by “brute force” approaches but by any existing heuristic approach as well.

In order to shrink the potentially huge size of the search space of GA, we reduced the number of weight coefficients encoded in chromosome to just *10*, by applying the following problem-specific knowledge:

- Experimental results suggest that the frequency spectra of both oscillating and non-oscillating driving feature a characteristic “long tail” pattern – the lower frequencies are represented by higher (i.e., more influential) amplitudes, while the amplitudes decrease with the increase of frequencies;
- The areas of higher frequencies (presumably, heavily influenced by the modelled irregularities of the road and non-ideality of the steering system of the car) of the spectrum of both oscillating and non-oscillating driving are quite similar. On the other hand, the patterns on the area of lower frequencies are more diverse, implying that the important discriminating features are more likely to be encoded in lower frequencies- rather than high-frequencies of the spectra;

- The frequencies that are above the Nyquist frequency (i.e., *25Hz*) would be under-sampled, and therefore, less-influential

Therefore, we divide all frequencies in PS into *10* variable-sized groups $G_1, G_2, \ldots,$ G_{10}, and assigned a respective weight coefficient $w_1, w_2, w_3, \ldots w_{10}$ to each of these groups. The size of groups (i.e., the number of included frequencies) increases gradually with the increase of the basic (minimum) frequency f_b of the group: in our approach, each group contains non-overlapping frequencies in the range $[f_b \ldots 1.25 \times f_b]$. This approach allows us with the increase of basic frequencies f_b of the groups $G_1, G_2, \ldots, G_{10}$, to gradually increase the group size and, consequently, to gradually reduce the precision of "tuning" of amplitudes of the individual (less-influential) frequencies within these groups. The groups of frequencies of WPS are shown in Table 5.

Considering the defined groups of frequencies in the spectrum, the resulting WPS could be expressed by the following Equation (5):

$$WPS_{1\sim44} = w_1 \times A_1^2 + w_2 \times (A_2^2 + A_3^2) + w_3 \times (A_4^2 + A_5^2) + w_4 \times (A_6^2 + \ldots + A_8^2) + w_5 \times (A_9^2 + \ldots + A_{11}^2) + w_6 \times (A_{12}^2 + \ldots + A_{15}^2) + w_7 \times (A_{16}^2 + \ldots + A_{20}^2) + w_8 \times (A_{21}^2 + \ldots + A_{26}^2) + w_9 \times (A_{27}^2 + \ldots + A_{34}^2) + w_{10} \times (A_{35}^2 + \ldots + A_{44}^2) \ldots \quad (5)$$

Where, *WPS* is the weighed power spectrum in a frequency range between *1Hz* and *44Hz*, A_i are the amplitudes of frequencies iHz $(i=1 \ldots 44)$ in the spectrum of Fourier-transformed signal, and w_k ($k=1 \ldots 10$) are the evolved (through GA) weight coefficients associated with each of the considered *10* groups of frequencies.

Table-5: Groups of frequencies of WPS

Frequency group	Frequencies included in the group	Size of the group	Corresponding weight coefficient in WPS
G_1	1Hz	1	w_1
G_2	2 Hz, 3 Hz	2	w_2
G_3	4 Hz, 5 Hz	2	w_3
G_4	6 Hz ~ 8 Hz	3	w_4
G_5	9 Hz ~11 Hz	3	w_5
G_6	12 Hz ~ 15 Hz	4	w_6
G_7	16 Hz ~ 20 Hz	5	w_7
G_8	21 Hz ~ 26 Hz	6	w_8
G_9	27 Hz ~ 34 Hz	8	w_9
G_{10}	35 Hz ~ 44 Hz	10	w_{10}

7.2.2. Genetic Operations

We employed binary tournament selection – proven to offer a good trade-off between the diversity of population and rate of convergence of fitness. In addition to the tournament selection, we also adopted elitism in that the two best-performing individuals always survive unconditionally into the mating pool of the next generation. In addition, we implemented two-point crossover and a single-point mutation. After each crossover and mutation operations, the chromosome is "repaired" by normalization so that the sum of all coefficients $w_1+w_2+w_3+ \ldots +w_{10}$ is equal to *100*. Notice that the range of the weights coefficient *[0..9]* that is applied during both (i) the creation of initial population and (ii) mutation, might be exceeded as a result of normalization of chromosomes that feature heavily fluctuating values of weight coefficients. The main parameters of GA are shown in Table 6.

Table-6: Main parameters of GA

Parameter	Value
Genotype	Ten weight coefficients $w_1, w_2, w_3, \ldots w_{10}$ of WPS, represented by real numbers within the range *[0..9]*. Each coefficient is discretized into *90* possible values.
Population size	100 individuals
Selection	Binary Tournament (10%)
Elite	Best 2 individuals
Crossover	Two-point
Mutation	Single-point (2%)
Fitness value	Minimum (among all *10* drivers) of the ratio (in %) of WPS of (i) inattentive (oscillatory) and (ii) attentive driving cases
Termination Criteria	(#Generations >100) or (Fitness Value >200) or (No improvement of fitness for 16 consecutive generations)

7.2.3. Fitness Function:

Because our objective is to evolve such WPS that allows for best possible discrimination of the signals of lateral acceleration of (i) inattentive (oscillatory) driving on straight section of the road from that of (ii) the fully attentive driving on cornering, the fitness value *F* of evolved chromosomes reflects the quality of such discrimination. In our approach, we consider the minimum of the ratios (in %) of WPS of these two driving cases among all *10* drivers, as described in Figure 25. The targeted fitness values *F* are the values that are higher than *100%* (i.e., indicating that WPS of inattentive driving is, indeed, *higher* than WPS of attentive driving even for the least-convincing driver). Higher fitness values would correspond to even better ability of WPS to discriminate the inattentive (oscillatory) driving from normal, attentive one.

```
for each driver d  do  {   // d = [Driver A, Driver B,…,Driver
 J]
    for each instant t of inattentive driving calculate WPSd_i(t);
    WPSd_i_max=max(WPSd_i (t));
    for each instant t of attentive driving calculate WPSd_a (t);
    WPSd_a_max=max(WPSd_a (t));
    Rd= WPSd_i_max / WPSd_a_max×100;
   }
F = min (RDriver_A, RDriver_B,…, RDriver_J);  // F: the fitness value
```

Fig-25: Fitness evaluation routine

7.3. Experimental Results

The fitness convergence characteristics of 20 independent runs of GA are shown in Figure 26. As illustrated, the fitness of the best-of run individuals, in average, increases from about 90 to about 121 in 64 generations. The best achieved fitness is 126, indicating that, even for the driver featuring most challenging ratio of canonical PS of inattentive and attentive driving (e.g., as depicted in Figure 28) the value of WPS of inattentive driving would be 26% higher than that of attentive one.

The values of the weight coefficients of sample evolved best-of-run individual (with fitness equal to126) are as follows:

w1=19, w2=1, w3=9, w14=1, w5=8, w6=3, w7=47, w8=10, w9=1, and w10=1

The values of WPS, obtained with these weight coefficients for all 10 drivers are shown in Figure 27. As Figure 27 depicts, for all of the drivers the WPS of inattentive driving on straight is higher than that of attentive driving on corners.

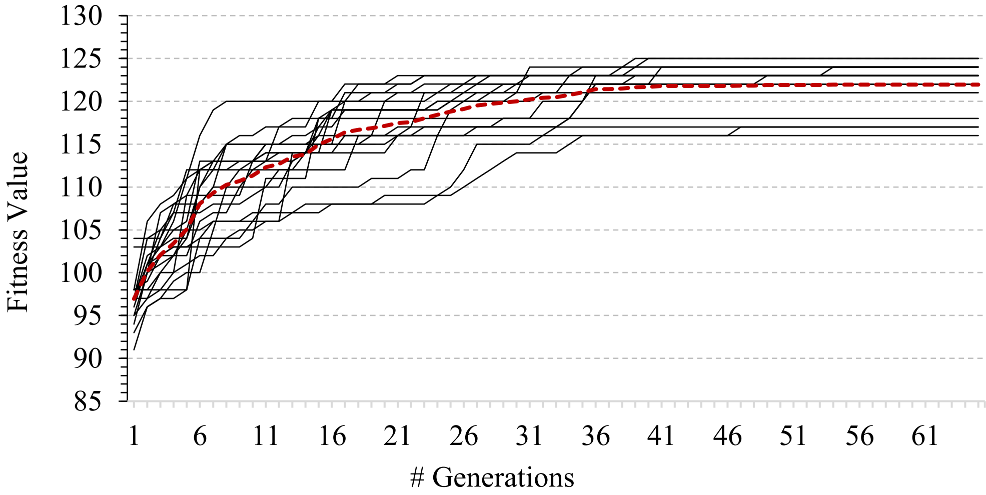

Fig-26: Convergence of the best-of-generation fitness of 20 independent runs of GA. The dashed line illustrates the average best-of-generation fitness of these 20 runs.

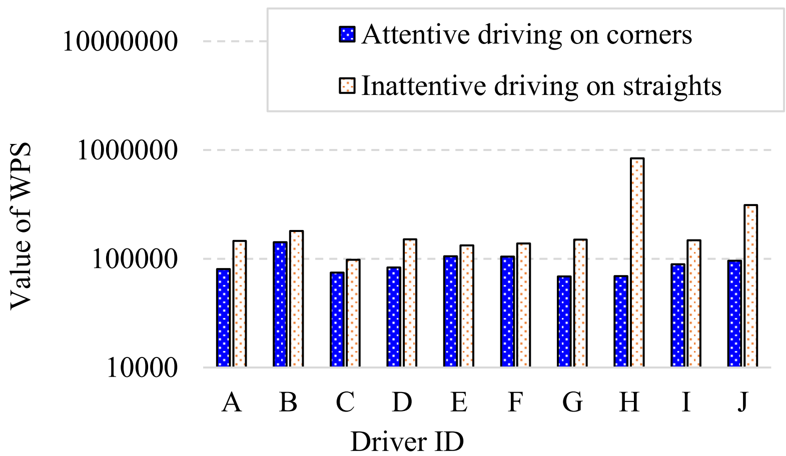

Fig-27: WPS of sample evolved best-of-run evolved weight coefficients. For all of the 10 drivers the WPS of inattentive driving on straights is higher than that of attentive driving in corners.

In contrast, as Figure 28 illustrates, with canonical PS, modelled as WPS with all weight coefficients w1, w2,…w10 set to 10, for 3 of the 10 drivers (e.g., Drivers C, D and E) the values of PS of inattentive driving on straight is anomalously lower than that of attentive driving on corners.

The dynamics of the instant values of WPS of both attentive and inattentive driving in the most challenging driving case (i.e., Driver C) are illustrated in Figure 29.

Compared to the dynamics of canonical PS (refer to Figure 21b), the evolved WPS yields a better discrimination. Indeed, as Figure 27 depicts, the values of WPS during inattentive driving on straight is higher (rather than lower, as in the case of canonical PS) than that of attentive driving in corners.

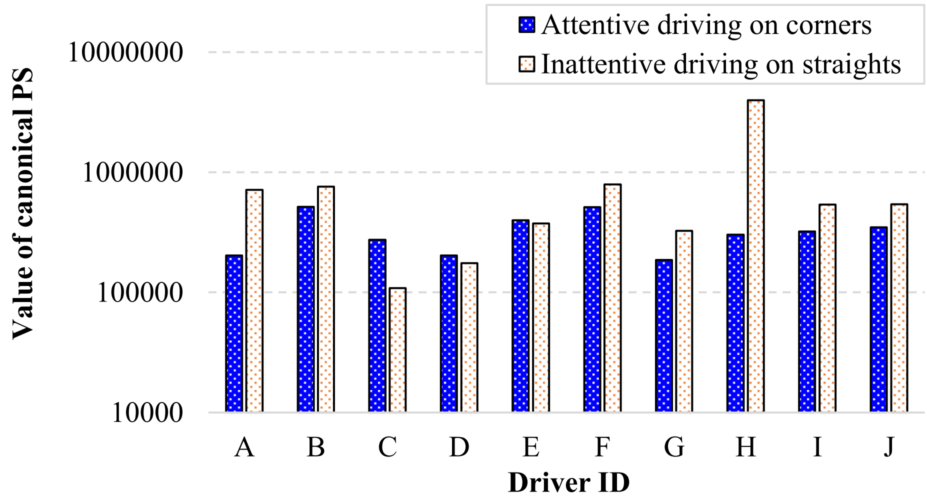

Fig-28: Canonical PS for 3 of the 10 drivers – Drivers C, D and E – the values of PS of inattentive driving on straight is anomalously lower than that of attentive driving in corners

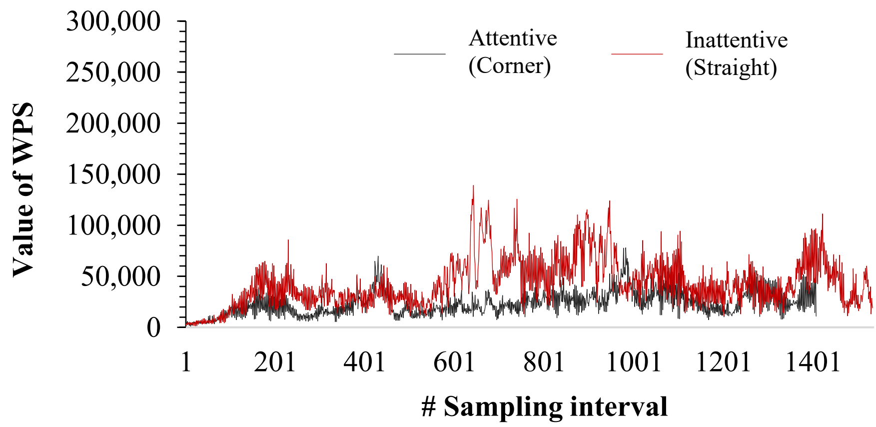

Fig-29: WPS of lateral acceleration of car driven by Driver C inattentively (on straight section of the road) and attentively (in corners). WPS features sample best-evolved (through GA) weight coefficients

7.4. Discussion

The eventual real-world implementation of the proposed approach of detecting the inadequate cognitive load from the WPS of oscillating lateral acceleration of the car implies that the challenge of variability of patterns of lateral acceleration should be addressed. These patterns might vary depending on the speed of the car, road conditions (turning radiuses of corners, etc.), personal driving styles, etc. While the effect of speed on lateral acceleration of cars is known and therefore, could be easily factored out by variable (depending on the speed of the car) scaling of the values of the obtained WPS, dealing with human-related factors could be much more challenging. The features of driving style (especially, the way of applying the error-correcting steering input) of the drivers are both (i) rather individual and (ii) naturally fluctuating (with time, condition of the car, road, and driver). Consonant with the hypothesis that the "average" human-related features are virtually non-existent, the experimental results confirm that the obtained values of WPS for each of the drivers vary significantly (Figure 27). Consequently, using the same threshold for discriminating the WPS that corresponds to different cognitive load of *all* drivers would be unfeasible. Rather, either a (static) threshold that is "learned" individually per particular driver, or, a dynamic threshold based on recently sensed state of the car or (and) driver might prove to be a better solution. In the latter case, we anticipate that the change of the WPS while driving, rather than its absolute value would be more symptomatic of the current cognitive load of driver.

Also, an improved robustness of recognition of inadequate cognitive load could be achieved by "learning" of weight coefficients of WPS on wider range of driving situations and road conditions. Ultimately, the quality of recognition of learned WPS should be verified on unknown set of driving situations and road conditions. This could be the part of the work to be done in the future.

Finally, an eventual failure to detect inadequate cognitive load from WPS of – presumably oscillating – lateral acceleration might not be necessarily associated with the inferiority of the proposed approach. Rather, even when distracted by texting, some drivers may still be able to control the car adequately, without suffering from any steering oscillations. Therefore, compared to other methods (e.g., based on eye tracking) that also attempt to infer the distracted driving, the proposed approach could be viewed as a holistic one, because it is based on detection of the actual effects of distractions on driving (i.e., steering oscillations, if any), rather than underlying reasons for these distractions.

Chapter - 8

Individually Adaptive Method for Oscillation Detection

8.1. Introducing Lateral Jerk

The other direction that we seized towards addressing the limitation of the initial methodology proposed in Chapter 6 is individually adaptive model. This model is based on the concept of lateral jerk. Lateral Jerk is defined as the first derivative of lateral acceleration. As mentioned previously in multiple occasion, we hypothesize that because the magnitude and corresponding frequency of the oscillating signal would differ from those of the normal signal, the resulting value of the power spectrum would be diverse (presumably higher) as well. For most of the drivers, the PS of inattentive (oscillating) driving even along straights is indeed higher than that of attentive driving around corners.

However, the preliminary experimental results also suggest that, occasionally, the PS of inattentive driving on straightaways could be lower than that of attentive driving around corners. This is a result of the diversity of driving conditions (straightaway, corner entry, steady-state cornering, and corner exit) and driver-dependent features of the acquired signals. The PS of attentive driving when cornering could be anomalously high because of extensive (yet, non-oscillating) steering wheel motions at corner entrances and exits. Figure 30 illustrates that for a sample driver, the PS of inattentive driving on a straightaway is lower than that of attentive driving around corners. As shown in the figure, an eventual fixed threshold set to 5×10^4 would allow us to detect inattentive driving on straightaways (Figure 30, Threshold T_{F1}). However, the PS of attentive driving when entering and exiting a corner would surpass this threshold as well, resulting in false positive detection of inattentive driving as shown in the Table 7. Setting the threshold to 2.8×10^5 (Figure 30, Threshold T_{F2}) would allow us to avoid false positive identifications; however, it would result in an inability to detect inattentive driving too (false negative).

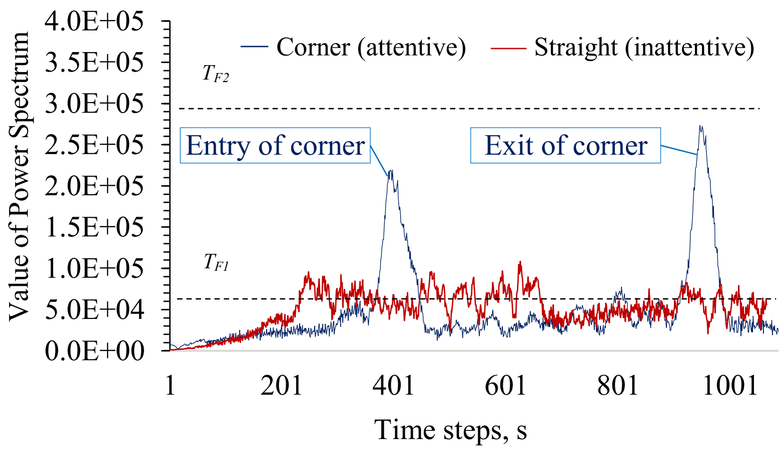

Fig-30: PS of the lateral acceleration of a car driven inattentively along straightaways and attentively around corners.

Table-7: Classification of driving conditions

Actual Driving Condition	Predicted Driving Condition	
	Attentive	Inattentive
Attentive	True Positive (TP)	False Negative (FN)
Inattentive	False Positive (FP)	True Negative (TN)

Table 7 illustrates the conditions for the classification of attentive and inattentive driving. It shows the mechanism of classifying the driving cases as True Positive (actual – attentive case, predicted – attentive case), False Positive (actual – inattentive case, predicted – attentive case), True Negative (actual – inattentive case, predicted –

inattentive case), and False Negative (actual – attentive case, predicted – inattentive case). Figure 31 shows the block diagram of this approach.

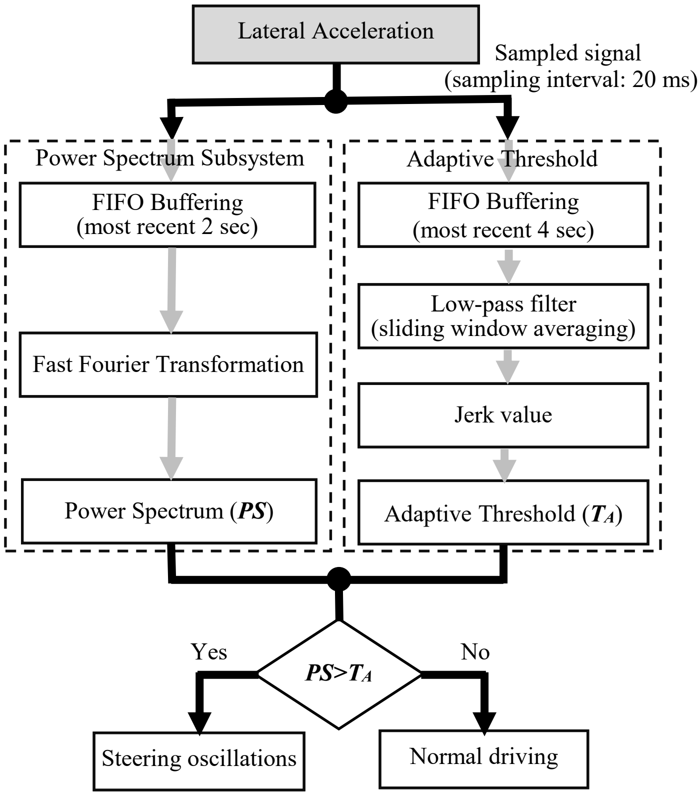

Fig-31: The block diagram of adaptive thresholding approach

The block diagram given in Figure 31 represents the method to identify steering oscillation (inattentive driving) based on adaptive threshold value. The model consists of two parallel subsystems that calculate the values of (i) the power spectrum and (ii) the adaptive threshold, respectively. Power spectrum subsystem comprises three modules: a FIFO buffer which stores the most recent 100 frames of the signal of lateral acceleration (2 sec), a fast Fourier calculation module, and a power spectrum calculation module. The adaptive threshold subsystem consists of a FIFO buffer which stores the most recent 200 frames of the signal of lateral acceleration (4 sec), a low pass filter (sliding window average), jerk value calculation module and adaptive threshold calculation module. The detection is done based on comparing the current value of adaptive threshold and PS. Both subsystems are synchronized in that they deal with the most recent samples of the row signal of the lateral acceleration of the car. The latency of the described model is 4 seconds, which corresponds to the real time, required to fill completely the longer of the two FIFO buffers – i.e., the buffer of the threshold calculation subsystem. The runtime overhead associated with the computation of the average values of lateral acceleration, jerk, Fourier transformation, and power spectrum are in order of few hundreds milliseconds, and therefore, have very little effect on the overall latency of the implemented model. The following subsection discusses the detail of this approach.

8.2. Adaptive Threshold based on Lateral Jerk.

In order to automatically adapt the threshold of the PS to different driving situations, we consider an approach for maintaining a basic minimal threshold value on straight and steady-state cornering, and we elevate this value for corner entrances and exits. An elevation of the threshold value could be implemented depending on whether corner entrances and exits are currently detected. A corner entrance is characterized by a movement of the steering wheel towards the corner, which results in an increase in lateral acceleration from approximately zero to some finite value that corresponds to the speed of the car and the steady turning radius of the corner. Similarly, at the corner exit, the driver returns the steering wheel to the default position, which results in a decrease in lateral acceleration from a finite, non-zero value that corresponds to steady-state cornering to zero. These changes in the values of lateral acceleration at corner entrances and exits can be expressed quantitatively as a derivative of lateral acceleration, or lateral jerk. In our approach, we utilize the absolute value of the jerk of smoothed lateral acceleration as an indication that the car is entering or exiting a corner. Consequently, the absolute value of the jerk is used as a factor that determines the corresponding increase in the adaptive threshold of the PS:

$$T_A = T_B + k \times \left|\frac{dA}{dt}\right| \ldots \qquad (6)$$

Where, T_A is the value of the adaptive threshold of the PS, T_B is the basic value, k is a coefficient, and dA/dt is the lateral jerk obtained as a derivative of the smoothed lateral acceleration, A. The mechanisms used to define these parameters are explained below.

In order to obtain a smoothed value of lateral acceleration, A, we employed low-pass digital filtering to the lateral acceleration signal of the car. Filtering is implemented by means of sliding window averaging of the most recent discrete samples of the lateral acceleration signal. The rationale for applying such a simple smoothing technique satisfies our intentions to filter out the relatively fast, driver-induced steering oscillations (occurred because of eventual inadequate cognitive engagement) while preserving the relatively slow steering input from the driver at corner entrances and exits. The mechanism for filtering instances *#1*, *#2*, *#3*, and *#n-k+1*, where k is the averaging factor of the time series of the lateral acceleration signal, a, can be expressed by equations (7), (8), (9), and (10), respectively.

$$A_1 = \frac{1}{k}(a_1 + a_2 + a_3 + \cdots + a_k) \ , \qquad (7)$$

$$A_2 = \frac{1}{k}(a_2 + a_3 + a_4 + \cdots + a_{k+1}) \ , \qquad (8)$$

$$A_3 = \frac{1}{k}(a_3 + a_4 + a_5 + \cdots + a_{k+2}) \ , \qquad (9)$$

$$\ldots$$

$$A_{n-k+1} = \frac{1}{k}(a_{n-k+1} + a_{n-k+2} + a_{n-k+3} + \cdots + a_n) \qquad (10)$$

We determined the size of the sliding window, k, by considering the fact that insufficiently low values of k would result in ineffective filtering. Ineffective filtering would not allow for sufficient dampening of driver-induced steering oscillations (with periods between 1–3 s) and noise that results from the imperfections in the steering system of the car (periods shorter than 1 s). Conversely, too high value of k would be associated with overly strong filtering that may eventually result in loss of the slow (period between

5–10 s) steering input pertinent to steady state cornering. In addition, an outsized window would be associated with increased latencies in obtaining the average values. Therefore, we consider the size of sliding window to be $k = 200$. This value accommodates discrete samples of lateral acceleration from the most recent 4 s of driving as a feasible trade-off that results in good filtering of the steering oscillation, noise, and reliability in preserving the steering patterns pertinent to the entering and exiting the corners. The mechanism used for obtaining the smoothed value of lateral acceleration, A, and lateral jerk from the raw lateral acceleration signal from one of the drivers, is illustrated in Figure 32a, 32b, and 32c.

The values of parameters T_B and k in Equation (6) are defined as follows. First, we define the basic minimal value of the adaptive T_B from attentive driving along a straightaway. Due to the naturally low values of lateral jerk when driving along straightaways, the second additive component in Equation (6) is much less influential than T_B. We set T_B to the minimum value that ensures zero false positive detections of cognitive load on straightaways, i.e., the PS of all attentive drivers on straightaways is below the value of the adaptive threshold, T_A. In our approach, $T_B = 1\times10^4$

After defining the value of T_B, we determine the value of the scaling factor, k, in Equation (6). The scaling factor is determined to be such that it results in a maximum summation of true positives and true negatives in the remaining cases of inattentive driving on straightaways, and for inattentive and attentive driving on corners (for all drivers). We found that setting the value of k equal to 2×10^4 satisfies this condition.

The mechanism used for applying the adaptive threshold for attentive driving on straightaways and around corners is illustrated in Figure 32d. As illustrated, the threshold increases in sync with the PS increases at corner entrances and exits, and stays well above the PS during the entire time trial. Conversely, as Figure 32e demonstrates, the value of

PS briefly exceeds the adaptive threshold in several instances in the middle of the corner and at its exit, indicating the successful detection of inattentive driving.

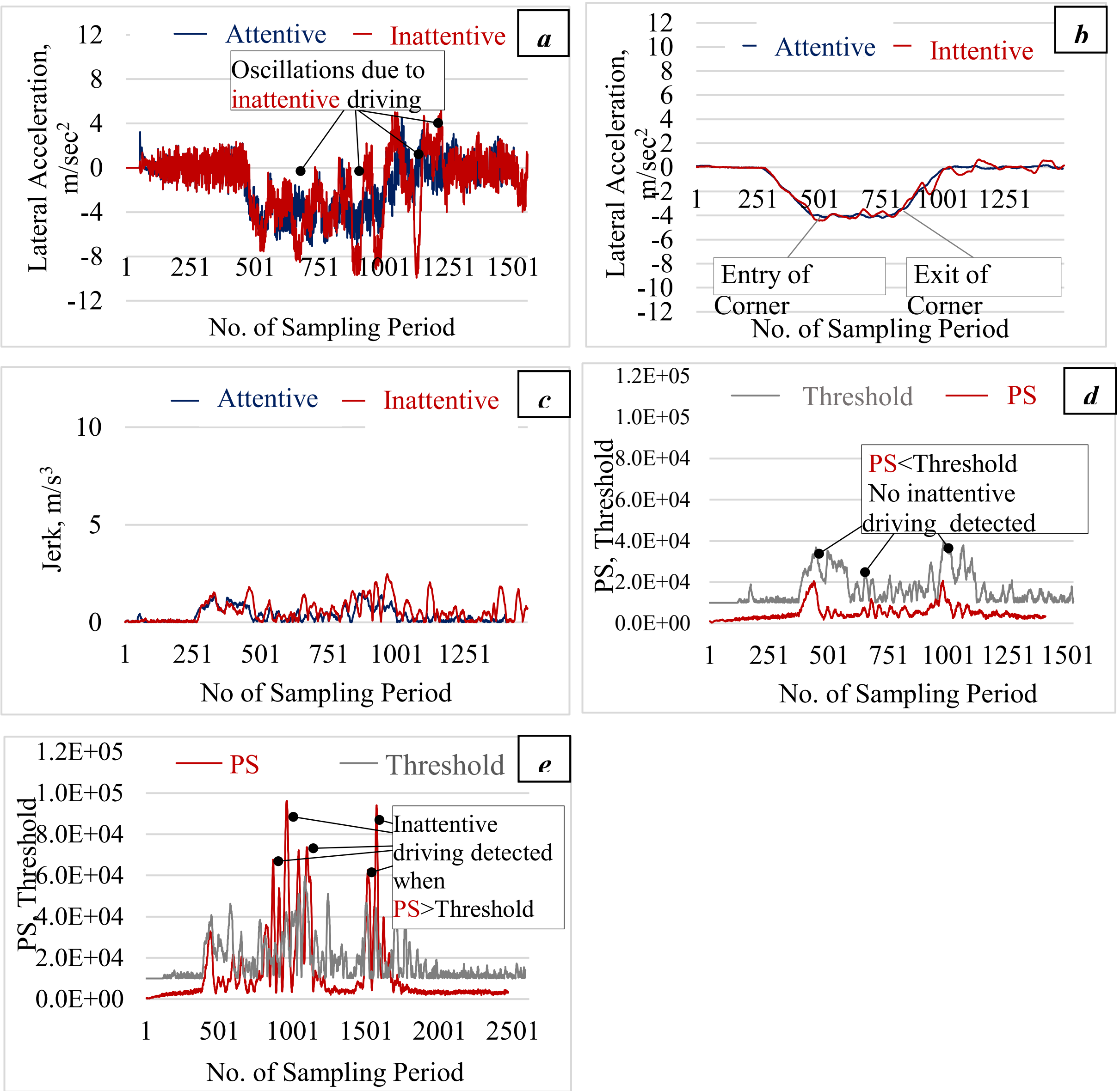

Fig-32: Dynamics of lateral acceleration (a), smoothed lateral acceleration (b), lateral jerk (c), PS and adaptive thresholding during attentive (d) and inattentive driving (e), respectively. The duration of sampling interval is 20 ms.

8.3. Experimental Results

The experimental results for the PS and adaptive threshold of attentive (a) and inattentive (b) driving on straightaways is shown in Figure 33 for all drivers. As depicted, the PS does not exceed the threshold in any straightaway driving scenario, resulting in zero cases of false positive inattentive driving detection (Figure 33a). However, for inattentive driving, the PS is lower than the threshold for three of the drivers (Drivers #3, #4, and #7), resulting in false negative detections (Figure 33b). The analogical results for corner driving are illustrated in Figure 34. In one of the attentive driving cases involving cornering, the PS exceeds the threshold (Driver #2, Figure 34a). For inattentive driving, only one of the drivers (Driver #1) features a PS that is lower than threshold (Figure 34b).

The overall accuracy of the proposed approach is estimated according to the following Equation (11):

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \times 100\%\,, \qquad (11)$$

Where, *TP, FP*, *TN*, and *FN* denote true positive, false positive, true negative, and false negative, respectively. As shown in Table 8, the accuracy of the proposed approach for adaptive thresholding is 88%, which is superior to the optimal accuracy of the approach based on fixed PS thresholding.

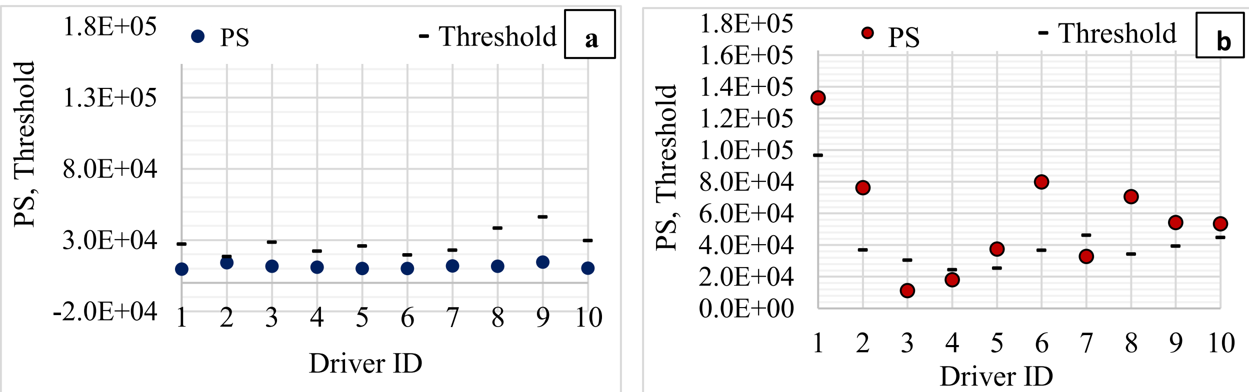

Fig-33: PS and adaptive threshold of attentive (a) and inattentive (b) driving on straightaways

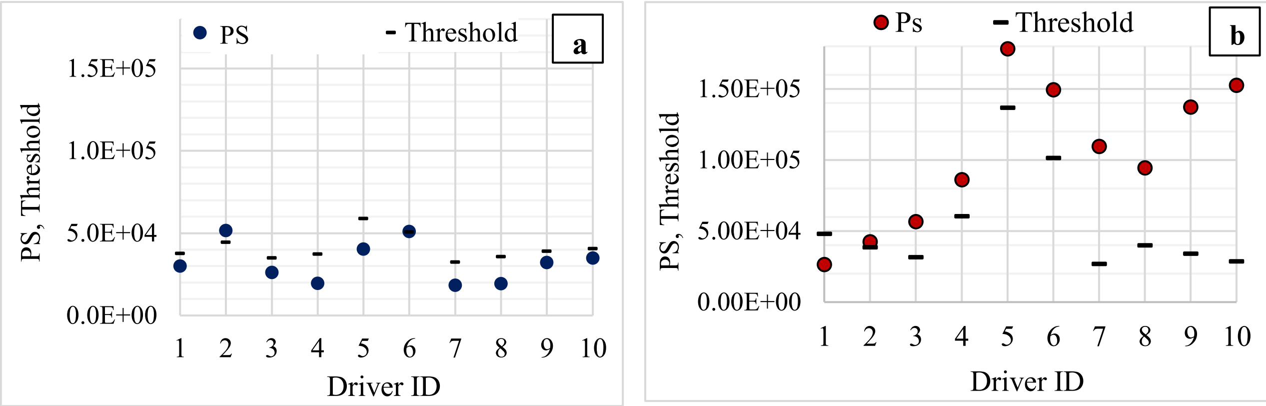

Fig-34: PS and adaptive threshold of attentive (a) and inattentive (b) driving around corners.

Table-8: Detecting accuracy of the cognitive load on drivers for different values of the threshold. FP, TP, FN, and TN denote false positive, true positive, false negative and true negative, respectively

Threshold		Driving situation								Accuracy
		Straight				Cornering				
		Attentive		Inattentive		Attentive		Inattentive		
		FN	TP	FP	TN	FN	TP	FP	TN	
Fixed	1.5×10^4	2	8	1	9	10	0	0	10	68%
	2×10^4	0	10	2	8	8	2	0	10	75%
	3×10^4	0	10	2	8	6	4	1	9	78%
	4×10^4	0	10	4	6	3	7	1	9	80%
	5×10^4	0	10	4	6	2	8	2	8	80%
	6×10^4	0	10	6	4	0	10	3	7	78%
Adaptive		**0**	**10**	**3**	**7**	**1**	**9**	**1**	**9**	**88%**

8.4. Discussion

The experimental results confirm that the obtained PS values for each driver vary significantly (Figures 33 and 34). Consequently, using the same mathematical model shown in Equation (6) with the same values of T_B and k to adjust the threshold for all drivers would be unfeasible. Instead, an adaptive threshold that is obtained from a mathematical model that is dynamically "tuned" (calibrated) individually per driver might prove to be a better solution. In addition, adopting the same mathematical model for all drivers might be unnecessary. Within the context of the non-existent average, the drivers use individually adjusted rather than “average” positions of the seat, headrest, steering wheel, and mirrors when they drive the car. Therefore, by conducting the experiment with just 10 arbitrary drivers, we intended to verify the feasibility of using the PS for the detection of inadequate cognitive load. This was conducted mainly for arbitrary drivers that attended the experiment. Despite the fact that we consider a single mathematical model for threshold adaptation, we still consider the quest for a single, general solution that would fit all drivers to be implausible.

Another concern of our research might be associated with the relatively long latency associated with determining the presence (or absence) of steering oscillations. This latency is a direct consequence of adopting sliding window averaging with a window length that accommodates 4 s of the most recent samples of lateral acceleration. However, we believe that faster detection of steering oscillations would be extremely challenging. This is because in the first few seconds, when the driver applies steering input, the oscillation-detecting system would be unable to determine whether a fully attentive driver normally steers into a corner, or is simply being inattentive. In both cases, the driver introduces oscillations. These two cases could be identified a few seconds later, depending on whether the steering inputs and the corresponding values of lateral acceleration remain relatively smooth (corresponding to the steady state cornering) or oscillate around some median value.

Finally, an eventual failure to detect inadequate cognitive load from the PS of lateral acceleration (presumably oscillating) might not be necessarily associated with the inability to detect inadequate cognitive load in drivers. Rather, even when distracted by texting, some drivers may still be able to adequately control the car without suffering from the effects of any steering oscillations. As Figure 33 illustrates, the PS of a car driven by Driver #3 is virtually the same, regardless of whether the driver is attentive or not (one of the three false negative cases, illustrated in Figure 33b).

On the other hand, the false positive case observed when driving around corners (attentive Driver #2, Figure 34a) could be somehow caused by motion sickness experienced by Driver #2. Therefore, compared to other approaches that attempt to identify distracted driving (e.g., approaches based on eye tracking, mind wandering, etc.); the proposed method could be seen as holistic. This is because it is based on detection of the actual effects that distractions have on driving rather than on the underlying reasons for these distractions. Moreover, because of its holism, the proposed approach could be applied to the detection of inadequate cognitive load that does not exhibit any visible symptoms. For example, day dreaming, erratic driving by cognitively impaired drivers, or driving under the influence of alcohol or drugs could be detected.

Further, different experiments that we performed during the study has reveal that oscillation could be detected in real time environment with few selective features. i.e. if those feature could be detected, we could identify the case of inattentive (oscillation) driving and attentive (non-oscillating) driving. Therefore, the following chapter discuss about the same approach of real-time detection by identifying the selective features.

Chapter - 9

Real-time Implementation of the Method

9.1. Introducing Real-time Detection Model

We have further tested the robustness of our model by implementing it to the real time application. Although we could have implemented the model as is, we further made a "*tuning*" in our previously proposed model so that it could be much faster and easier in real time implementation. Real time detection model is based on detecting the relevant feature of the signal of absolute value of lateral jerk, which came as the learning from different experiments during the process of studying steering oscillation. The main difference in this model is that, this model does not rely on Fourier transformed signal and PS like in previous approach. Since those process are not involved, this model is relative faster in computational process and thus, ideal for real time implementation.

9.1.1. Features of Steering Oscillations

The various experimental result provided us the intuition on aggregating the features of the steering oscillation; we believe that identifying these features would help us identifying the steering oscillation induced due to inadequate cognitive load. Those features are further discussed below in section 9.1.1.1:

9.1.1.1. Number of Pulses

We viewed the number of major peaks of lateral jerk during both oscillating and non-oscillation case as the pulses. The comparison of pulses in per unit of time in both the cases shows that the count of major pulses is higher in oscillating driving cases. The Figure 35, shows that during 7 second of non-oscillating cornering at the speed of 40 km/hr, there are only two pulses of lateral jerk i.e. one at the entry of the corner and another at the exit of the corner. The Figure 36, shows oscillating driving case where the count of the pulses is six.

9.1.1.2. Amplitude of Pulses

As we can clearly visualize in both Figure 35 and Figure 36, that the major pulses due to significant movement of steering wheel could be discriminated from minor pulses due to smaller adjustments of steering wheel by both amplitude and duration.

9.1.1.3. Interval between Pulses

The period between major pulses, pertinent to normal steering behaviour is long. As both Figure 35 and Figure 36 illustrate, the period between the two major pulses (one pulse at the entry- and another one – at the exit of the corner), pertinent to non-oscillating driving is about 5.5 ~ 6 seconds. Conversely, during oscillating driving the interval between major pulses is shorter – about 1~1.5 seconds.

9.1.1.4. High-frequency Oscillation in Pulses

The major pulses pertinent to non-oscillatory driving at the entry of the corner features a high-frequency oscillations. We believe that these oscillation illustrate the transition processes in turning and are caused by the elasticity of the sidewall of the tires.

These oscillations could be seen other major pulses in both non-oscillating (Figure-35) and oscillating (Figure-36) driving. They might not be related to the presence (or absence) of steering oscillations, and are of much higher frequency than the latter.

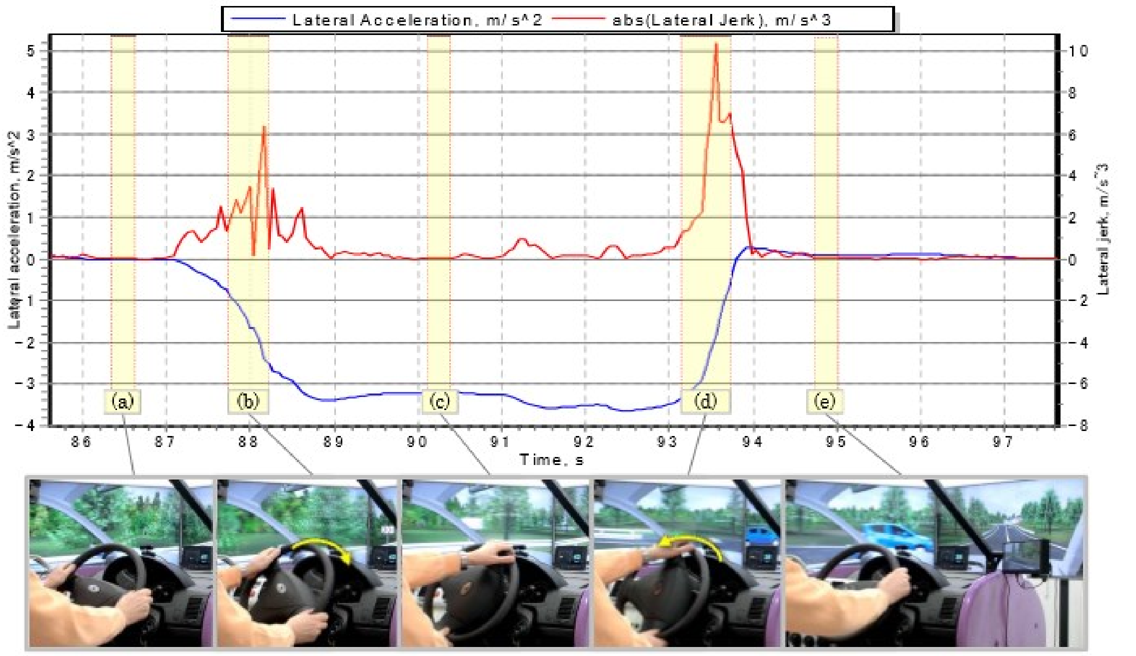

Fig-35: The pattern of lateral acceleration and absolute value of the lateral jerk of the car during normal (non-oscillating driving) in a right corner

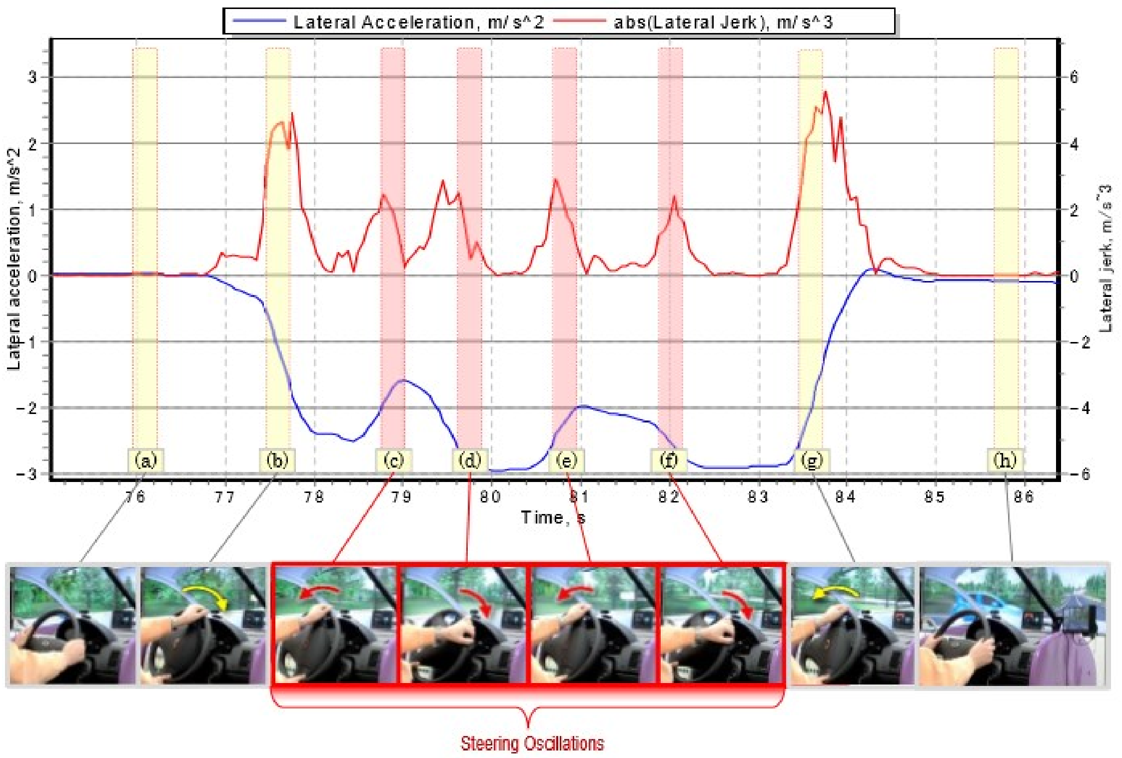

Fig-36: The pattern of lateral acceleration and absolute value of the lateral jerk of the car during oscillating driving in a right corner.

9.1.2. Detecting the Features of Steering Oscillation

We intend to detect steering oscillation in real-time by detecting the relevant features. Regarding our first features, we count the number of major pulses for a period and once the count reached to a given number, the oscillations is assumed to be detected. Similarly, amplitude of the pulses indicates that the counting should be done only of the major pulses that exceeds some threshold. The other feature, interval between pulses, indicates that the oscillation occurs in a continuous series within a specific time interval. Therefore, we try detecting based on detecting window, which prevent detecting irrelevant high-frequency oscillation, and signals that are pertinent to normal steering during cornering. The basic block diagram of our approach is shown in Figure 37. The algorithm and the pseudocode of implementation of the proposed real-time detecting mechanism are discussed in the following subsection:

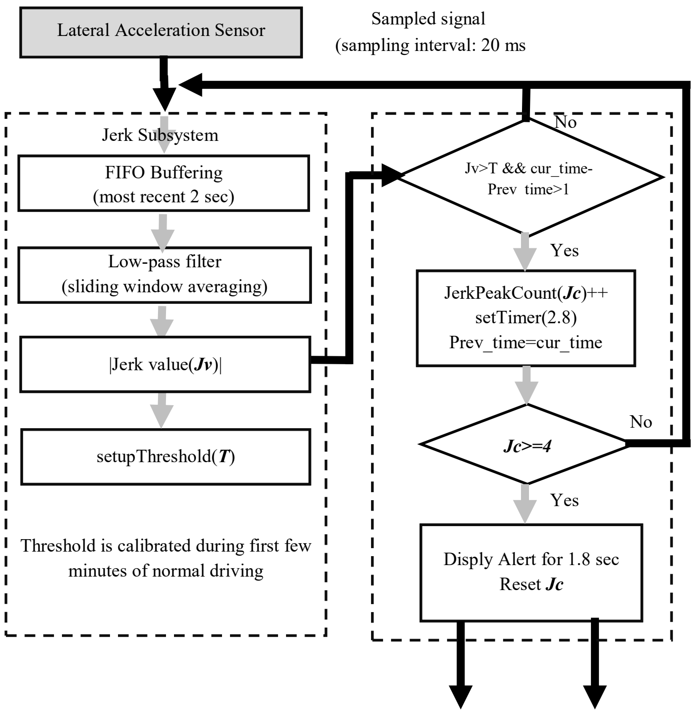

Fig-37: The block diagram of real time detection model

The Figure 37 shows the block diagram of the model. This approach is relies on counting the number of peak of the lateral jerk signal. As seen in the figure, this model has Jerk Sub-system model, which is responsible for performing two operation. (i) Calibrating the static threshold from the normal driving signal (or this could be manually setup as shown in the pseudo-code in Figure 38) and, (ii) constantly analysing the signal to count the number of peaks above the threshold with in a period to alert the driver. The details of the algorithm is explain in the following subsection.

9.1.2.1. Algorithm for Real-time Oscillation Detection

The algorithm of detecting the steering oscillations that reflects the above-mentioned three aspects is illustrated in Pascal-like pseudo-code in Figure 38.

1) The counter of major pulses is denoted as a global variable *Jerk_Cnt* (Figure 38, line #1). The detection of oscillation is assumed when the value of the counter reaches 4.
2) The value used for thresholding of the values of lateral jerk is denoted as a local constant *Jerk_Threshold* = 2.4 (Figure 38, line #5).
3) The specific time interval "detecting window" of 1.8 seconds is maintained as an interval between 1 second (local constant *Interval_of_Insensitivity* = 1.0, Figure 38, line #6) and 2.8 seconds (the interval of counter resetting timer *Resetting_Timer* (Figure 38, line #15, and lines #20~#25) after the most recently detected major pulse.

Only pulses that have higher amplitude than *Jerk_Threshold* (Figure 38, line #11) and are detected within the "detecting window" (Figure 38, line #12) are counted by *Jerk_Cnt* (Figure 38, line #14). The procedure *Display_Jerk_Cnt_on_Dashboard_Indicator* (Figure 38, lines #18 and #24) displays the value of the *Jerk_Cnt* in the warning indicator as illustrated in Figure 39. Value of the counter equal to 4 is associated with detected oscillations.

```
(a)
// Global Variables:
1. Jerk_Cnt: integer=0;
2. Prev_Jerk_Timestamp_s: single=0;

(b)
3. Procedure Detect_Steering_Oscillation;        // Activates 50 times per second
4. const                                          // Local constants
5.    Jerk_Threshold = 2.4;                       // in m/s^3
6.    Interval_of_Insensitivity = 1.0;            // in seconds
7. var
8.    Current_Timestamp_s : single;               // Local variable
9. begin
10.   Current_Timestamp_s := Now;                 // Function "Now" returns the number of seconds after 00:00 of January 1, 1900
11.   if (abs(Driving_Agent.Perceptions.Lateral_Jerk) > Jerk_Threshold)
12.   and ((Current_Timestamp_s - Prev_Jerk_Timestamp_s) > Interval_of_Insensitivity)
13.      then begin
14.            inc(Jerk_Cnt);
15.            Enable_and_Restart_Resetting_Timer;          // Timer will be activated 2.8 seconds later
16.            Prev_Jerk_Timestamp_s := Current_Timestamp_s;
17.          end;
18.   Display_Jerk_Cnt_on_Dashboard_Indicator;              // Functionality of this function is illustrated in Figure 4
19. end;

(c)
20. Procedure Resetting_Timer Timer;                        // Activates 2.8 seconds after last restart (Line # 13)
21. begin
22.   Resetting_Timer.Enabled:=false;                       // Disabling the Resetting_Timer
23.   Jerk_Cnt:=0;                                          // Resetting the Jerk_Cnt
24.   Display_Jerk_Cnt_on_Dashboard_Indicator;              // Functionality of this function is illustrated in Figure 4
25. end;
```

Fig-38: Algorithm with pseudo-code for detecting steering oscillations.

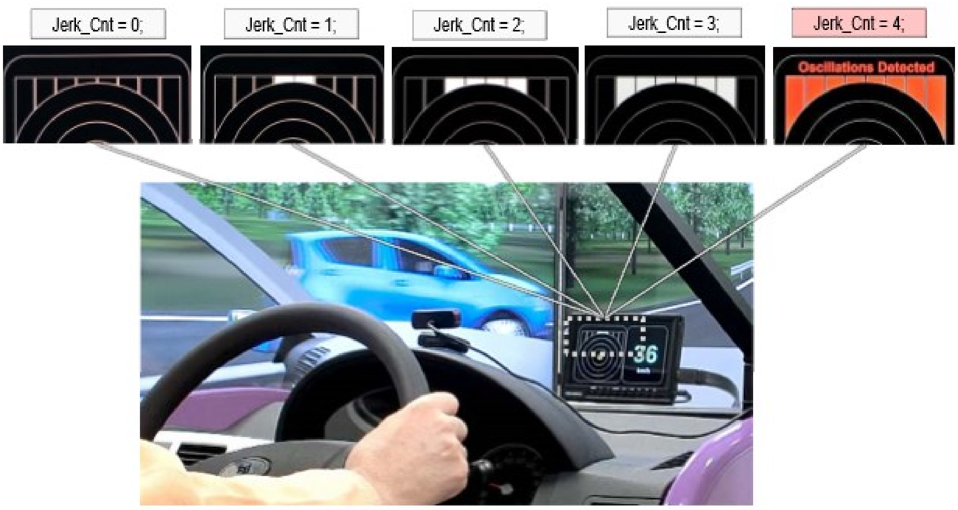

Fig-39: Displaying the number of counted peaks (value of the variable *Jerk_Cnt*) on the dashboard indicator by procedure *Display_Jerk_Cnt_on_Dashboard_Indicator*. The procedure is activated as shown in Figure 38, lines 18 and 24.

9.1.3. Experimental Result

The experimental results that verify the feasibility of the proposed approach to detect steering oscillations are illustrated in Figure 40, Figure 41, Figure 42, and Figure 43. These figures illustrate the detecting and counting (in the global variable *Jerk_Cnt*, Figure 38, line 14) of first, second, third and fourth major pulses during oscillatory cornering. The first (Figure 40) and the fourth (Figure 43) pulses correspond to normal steering at the entry and exit of corner, respectively. Second (Figure 41) and third (Figure 42) pulses, however, are a result of steering oscillations, and should not be there in a normal (non-oscillatory) cornering. The value of counted pulses equal to four indicates a detection of steering oscillations (Figure 43).

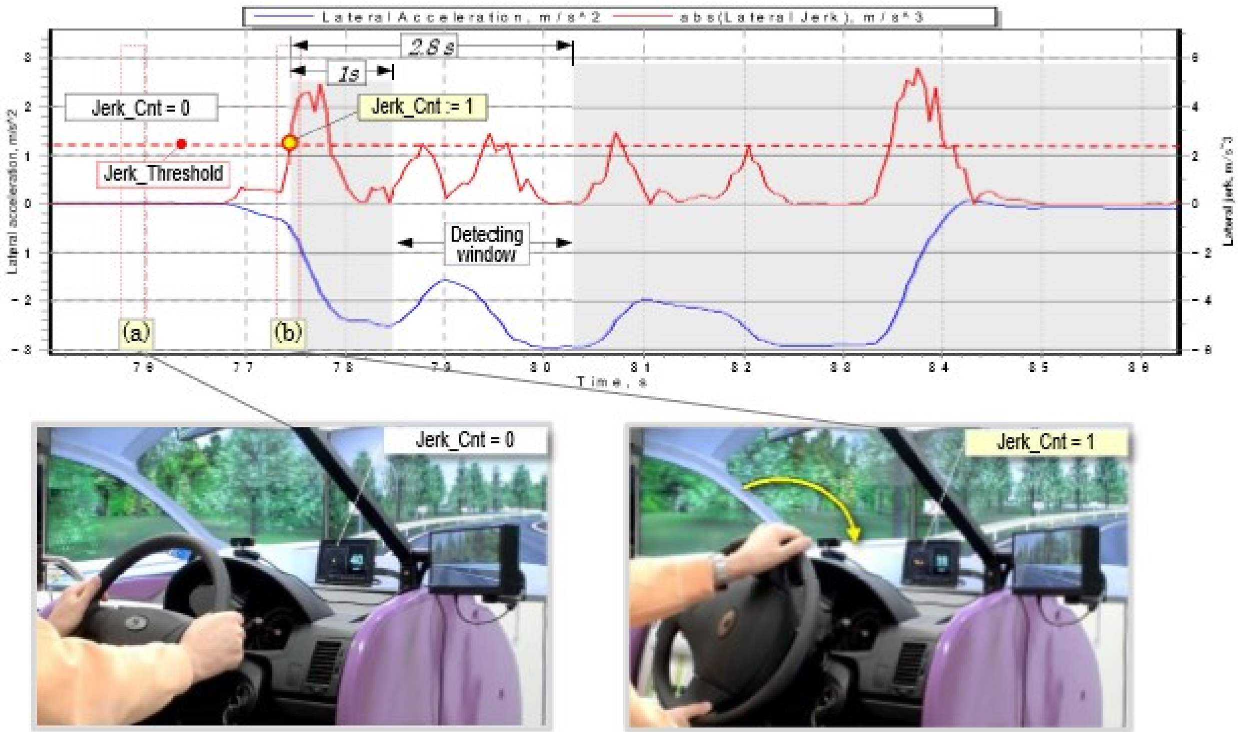

Fig-40: Detecting and counting the first major pulse (time 77.4s). The pulse corresponds to normal steering at the entry of corner.

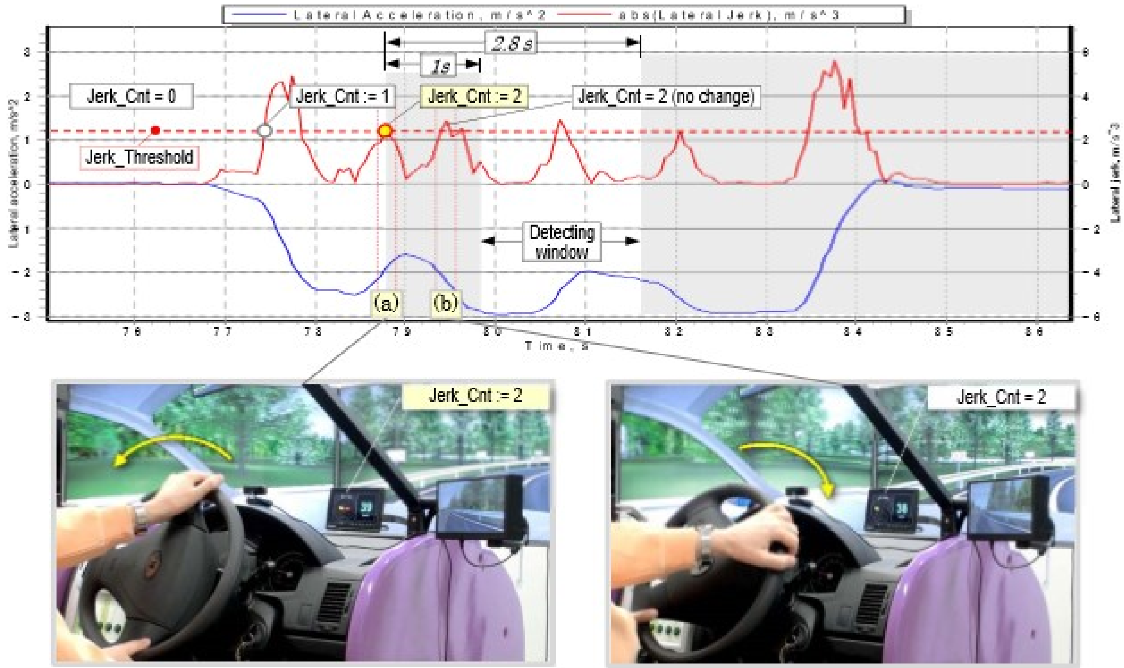

Fig-41: Detecting and counting the second major pulse (time 78.8 s). The pulse is detected and counted because its amplitude is higher than threshold, and because its timing fits within the detecting window. The pulse corresponds to steering oscillations during steady state cornering

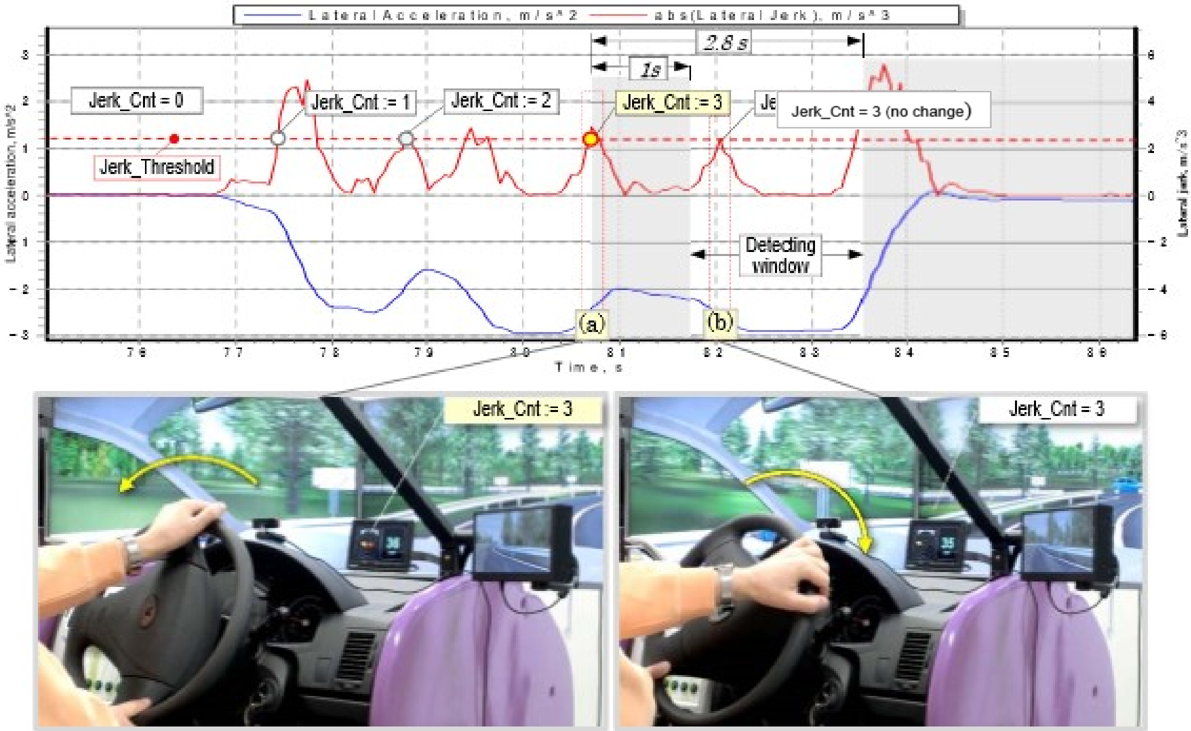

Fig-42: Detecting and counting the third major pulse (time 80.7 s). The pulse is detected and counted because its amplitude is higher than threshold, and because its timing fits within the detecting window. The pulse corresponds to the steering oscillations during steady state cornering

Fig-43: Detecting and counting the fourth major pulse (time 83.5 s).

The pulse is detected and counted because the amplitude is higher than threshold. In addition, its timing fits within the detecting window as well. The pulse corresponds to normal steering at the exit of the corner. However, due to the accumulation of the counted number of detected major pulses, the fourth pulse signals the detection of steering oscillations. Notice that the value of the counted pulses in normal, non-oscillatory driving would not exceed one in slow turns (when the timer will reset the counter to zero 2.8s after the detected first pulse). Also, it will not exceed two in fast turns (one pulse would be counted at the entry of the fast turn and one more pulse – if the interval between pulses is shorter than 2.8s – at its exit)

9.1.4. Robustness of Detection Model with Mobile Application

After successful implementation of the model in fully-fledged simulator. We further wanted to check the robustness of the model; therefore based on the same detection model we further implement it as a mobile application. The snapshot of the application are shown in Figure 44. This application requires manual calibration for few second in non-oscillating driving situation before using it for detecting the steering oscillation. Once, the application is calibrated, it setup the general threshold, which is constantly compared with the absolute jerk value to detect the steering oscillation. Since, it is possible to activate the oscillation detection during oversteering and under steering, as well as during lane changing; driver is however only alerted after surpassing the fixed maximum frequency of oscillation detection *(refer Figure 43)*.

Fig-44: Snapshot of oscillation detecting application in real-time testing (a), Detecting the oscillating intensity (b), Maximum oscillating intensity triggers alert (sound) to the driver (c).

After the detection of oscillation (continuous detection of major peak amplitude with in the given time), this application also beeps to alert the driver in order to signal inadequate cognitive engagement. The Figure 44a, shows the initial run of the application, however the calibration part is not shown in the figure. Figure 44b shows the detection of oscillation intensity. Likewise, Figure 44c shows that the oscillation intensity has reached the peak after which the driver is alerted with the beeping sound.

Chapter - 10

Summary, Conclusion, and Future Works

10.1. Summary

This study was initiated with the objective to formulate effective methodology to identify inattentive and/or distracted driving so that, millions of accidents that occurs because of inattentive and/or distracted driving around the world would be prevented. Therefore, to address these issues we introduced the concept of steering oscillation. We considered that, inadequate cognitive load of the driver will result in delay of response, and delay of response would result in delay in the feedback. Considering Nyquist criterion in control theory, we hypothesized that; delay in feedback would result in unstable or oscillating system. We believe that, once this hypothesis were verified we could further proposed the method for its detection. Therefore, we initially did experiments to verify the hypothesis that inadequate cognitive load of the driver result in delay in response of the driver, which ultimately resulted in steering oscillation. We verified our hypothesis in several stages of experiment. First, we verified the concept with driving agent evolved via genetic programming where, we deliberately introduce various delay in the steering response of the agent. We found out that such delay results in the oscillation of the car. After, the successful result with the driving agent, we continue experiment with different human driver by distracting each of them with messaging (texting while driving) to increase the cognitive load of the driver. The experiment with human driver also proved our hypothesis that increase in the cognitive load of the driver results in the steering oscillation.

The verification of our hypothesis motivated us to formulate method to identify the steering oscillation and detect the distracted driving. We devise detection mechanism by spectrum analysis. This detection mechanism was further optimized with genetic algorithm. We also introduced adaptive method of detection with lateral jerk. A tuned with feature identification and was implemented for real-time detection both in fully-fledged driving simulator and tested in real-time by developing a smart phone application.

We view the obtained results as a significant step towards the development of a system for early warning of the inadequate cognitive load of drivers in routine driving conditions – well before any urgent reaction to an eventual dangerous traffic situation might be needed.

10.2. Conclusion

We introduced the concept of steering oscillation and verified that it is induced as the result of inadequate cognitive load of the driver. To verify the concept we initially proposed, an approach that employs GP to develop automatically, a driving agent—as a model of a human driver—that optimally steers a realistically simulated car with non-latent steering response. We verified the hypothesis that a simulated delay in the steering response of the evolved model of a human driver results in well-expressed steering oscillations. In addition, the experimental results of the impact of speed on a computationally evolved driving agent highlight the robust nature of our approach. Further, it has also been observed that increase in speed increases the amplitude of the oscillation, thus underlining the extreme consequences of driving with inadequate cognitive engagement.

Additionally, we verified with real human drivers that the delay of response of the cognitively inattentive drivers (simulated via texting and driving) result in characteristic steering oscillations of the realistically simulated car in all of the considered three test cases – driving on straight, on entry and on exit of corner.

We also investigated an approach of automatically classifying the driver-induced steering oscillation of a simulated car driven by a cognitively inadequate human driver. The inadequate cognitive engagement of the driver is associated with delay of response, which, in turn, according to the control theory applied to the system driver-car, results in an oscillating steering behaviour of the car. In order to identify the inadequate cognitive load by resulting steering oscillations, we propose an approach of analysing the power spectrum of the lateral acceleration of the car. The experimental results suggest that the magnitude of the power spectrum could be used to classify the oscillating steering behaviour of the car for at least 8 out of 10 drivers by merely setting up the static threshold. However, we discovered that the patterns of the signals of lateral acceleration (and the values of the corresponding power spectrum of its Fourier transformation) of a car controlled by an inattentive driver along a straight road mimics the pattern of a cornering car even when driven by a fully attentive driver. Therefore, it would be unfeasible to apply thresholding to a canonical power spectrum featuring an equal (flat) weight coefficient for identifying inattentive driving from the presence of steering oscillations under all driving conditions. We hypothesized that optimization of the weight coefficients of the power spectra would enhance the detection of these steering oscillations and improve their discrimination from attentive driving when negotiating corners. Thus, we applied genetic algorithms to evolve the optimal values of the weight coefficients of the power spectrum. The experimental results verified that an evolved weighted power spectrum facilitates improved discrimination between oscillatory and non-oscillatory steering behaviour for all 10 tested human drivers even under challenging circumstances.

Further, we proposed additional method based on adaptive thresholding of the power spectrum magnitude of a Fourier-transformed time series, which is obtained from the lateral acceleration of a car. We utilized the lateral jerking motion of the car as a factor that directly determines the instantaneous value of the adaptive threshold. The experimental results suggest that adaptive thresholding of the power spectrum of lateral acceleration facilitates the detection of driver-induced steering oscillations (caused by inattentive driving due to texting on mobile phone) with an overall accuracy of 88%, in the test cases of driving of a car, realistically simulated in TORCS, on straightaways and around corners.

Finally, with multiple experiments, we were able to identify various features that could be detected in order to identify the oscillation in real time situation. We propose feature detection mechanism in real time situation. Also, tested this method in driving simulator and in real car with the version of smart phone application. Hence, we were able to achieve our three main objective. i.e. (i) to verify our hypothesis that delay in cognitive load of human driver result in delay in response, (ii) the delay in response result in delay in feedback, that ultimately effects in steering oscillation of the driver and, (iii) to find suitable mechanism to detect such oscillation with readily available sensors.

10.3. Future Work

Although we have performed substantial amount of experiments to verify our proposed approach, there are still multiple directions, which could be taken to further enhance this work. The continuation of this research could be (a) to explore the idea of varying the threshold of the weighted power spectrum (in real time) in a way that would allow the threshold to adapt dynamically both (i) to the driving style of drivers and (ii) to the specifics of driving situations. (b) Another interesting continuation would be, to accumulate various features from the model that we devise for the real-time detection, and instead of just identifying those feature by human defined logics, rather we could use machine learning approach (presumably GP, GA or SVM) to classify (or identify) the oscillating and non-oscillating driving conditions.

Similarly, for now we have tested our oscillation detection model with smart-phone application, however, it might not be practical for everyday use, as mobile phone itself act as a part of distraction. Therefore, instead of relying on mobile phone application, we could also design our proposed model for smaller embedded system like Arduino, raspberry pie, or could implement in more robust devices, so that it could act as a complete system that could be ready for any vehicle in order to identify the steering oscillation.

Another direction of this study is to extend it for identifying the drink and drive case. Many studies has shown that, drinking alcohol more than a certain limit would reduce the response time in the brain [58] [59] [60]. Hence, we believe that drinking and driving would also result in similar effects like in steering oscillation, which could be detected by using our existing approach; however, detail study and experiments are required to verify the results.

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Appendix

1. XML Schema for the evolved model of driving agent in XGP

```
<?xml version="1.0"?>
<xs:schema xmlns:xs="http://www.w3.org/2001/XMLSchema">


<xs:simpleType name="VAR">
  <xs:restriction base="xs:string">
    <xs:enumeration value="p_0"/>
    <xs:enumeration value="p_1"/>
    <xs:enumeration value="p_2"/>
    <xs:enumeration value="p_3"/>
    <xs:enumeration value="p_4"/>
    <xs:enumeration value="p_5"/>
  </xs:restriction>
</xs:simpleType>

<xs:simpleType name="CONST">
  <xs:restriction base="xs:integer">
    <xs:minInclusive value="0"/>
    <xs:maxInclusive value="10"/>
  </xs:restriction>
</xs:simpleType>


<xs:simpleType name="OP">
  <xs:restriction base="xs:string">
    <xs:enumeration value="+"/>
    <xs:enumeration value="-"/>
    <xs:enumeration value="*"/>
    <xs:enumeration value="/"/>
  </xs:restriction>
</xs:simpleType>


<xs:complexType name="STM2">
   <xs:sequence>
      <xs:element name="OP" type="OP"/>
      <xs:element name="STM" type="STM"/>
      <xs:element name="STM" type="STM"/>
    </xs:sequence>
  <xs:attribute name="ind" type="xs:integer" use="optional"/>
</xs:complexType>

<xs:complexType name="STM">
   <xs:choice>
```

```
      <xs:element name="STM2" type="STM2"/>
      <xs:element name="VAR" type="VAR"/>
      <xs:element name="CONST" type="CONST"/>
    </xs:choice>
  <xs:attribute name="ind" type="xs:integer" use="optional"/>
</xs:complexType>

<xs:element name="GP">
 <xs:complexType>
   <xs:sequence>
     <xs:element name="STM" type="STM"/>
   </xs:sequence>
   <xs:attribute name="ind" type="xs:integer" use="optional"/>
 </xs:complexType>
</xs:element>

</xs:schema>
```

2. XML Schema for optimising weight coefficient in XGA

```
<?xml version="1.0"?>
<xs:schema xmlns:xs="http://www.w3.org/2001/XMLSchema">

<xs:simpleType name="k_1">
 <xs:restriction base="xs:integer">
       <xs:minInclusive value="0"/>
       <xs:maxInclusive value="90"/>
 </xs:restriction>
</xs:simpleType>

<xs:simpleType name="k_2">
 <xs:restriction base="xs:integer">
       <xs:minInclusive value="0"/>
       <xs:maxInclusive value="90"/>
 </xs:restriction>
</xs:simpleType>

<xs:simpleType name="k_3">
 <xs:restriction base="xs:integer">
       <xs:minInclusive value="0"/>
       <xs:maxInclusive value="90"/>
 </xs:restriction>
</xs:simpleType>

<xs:simpleType name="k_4">
 <xs:restriction base="xs:integer">
       <xs:minInclusive value="0"/>
       <xs:maxInclusive value="90"/>
 </xs:restriction>
</xs:simpleType>

<xs:simpleType name="k_5">
 <xs:restriction base="xs:integer">
       <xs:minInclusive value="0"/>
       <xs:maxInclusive value="90"/>
 </xs:restriction>
</xs:simpleType>

<xs:simpleType name="k_6">
```

```
 <xs:restriction base="xs:integer">
       <xs:minInclusive value="0"/>
       <xs:maxInclusive value="90"/>
 </xs:restriction>
</xs:simpleType>

<xs:simpleType name="k_7">
 <xs:restriction base="xs:integer">
       <xs:minInclusive value="0"/>
       <xs:maxInclusive value="90"/>
 </xs:restriction>
</xs:simpleType>

<xs:simpleType name="k_8">
 <xs:restriction base="xs:integer">
       <xs:minInclusive value="0"/>
       <xs:maxInclusive value="90"/>
 </xs:restriction>
</xs:simpleType>

<xs:simpleType name="k_9">
 <xs:restriction base="xs:integer">
       <xs:minInclusive value="0"/>
       <xs:maxInclusive value="90"/>
 </xs:restriction>
</xs:simpleType>

<xs:simpleType name="k_10">
 <xs:restriction base="xs:integer">
       <xs:minInclusive value="0"/>
       <xs:maxInclusive value="90"/>
 </xs:restriction>
</xs:simpleType>


<xs:complexType name="STM">
   <xs:sequence>
      <xs:element name="k_1" type="k_1"/>
      <xs:element name="k_2" type="k_2"/>
      <xs:element name="k_3" type="k_3"/>
      <xs:element name="k_4" type="k_4"/>
      <xs:element name="k_5" type="k_5"/>
      <xs:element name="k_6" type="k_6"/>
      <xs:element name="k_7" type="k_7"/>
      <xs:element name="k_8" type="k_8"/>
      <xs:element name="k_9" type="k_9"/>
      <xs:element name="k_10" type="k_10"/>
    </xs:sequence>
  <xs:attribute name="ind" type="xs:integer" use="optional"/>
</xs:complexType>

<xs:element name="GP">
 <xs:complexType>
   <xs:sequence>
     <xs:element name="STM" type="STM"/>
   </xs:sequence>
   <xs:attribute name="ind" type="xs:integer" use="optional"/>
 </xs:complexType>
</xs:element>

</xs:schema>
```

3. Program Source Code

The source code for the programs used in this study are available in the enclosed CD.

Publications

Journal Papers

- Dipak G. Sharma, Ivan Tanev, and Katsunori Shimohara, "*Detecting Driver-induced Steering Oscillations through Adaptive Thresholding of the Power Spectrum of Vehicle's Lateral Acceleration*", Institute of Electrical Engineers of Japan (IEEJ) Transactions on Electronics, Information and Systems (IEEJ TEIS), Vol. 138, No. 3, pp. 254-262, 2017

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- Dipak Gaire Sharma, Rahadian Yusuf, Ivan Tanev, and Katsunori Shimohara, *"Evaluation of Genetic Programs in Multiple Cases Evolved for Gait Classification and Recognition"*, Institute of Electrical Engineers of Japan (IEEJ) Transactions on Electronics, Information and Systems, Vol. 136, No. 9, pp. 1400-1410, 2016

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- Dipak. Sharma, Rahadian Yusuf, Ivan Tanev, and Katsunori Shimohara, *"Evaluation of Genetic Programming in Multiple Cases Evolved for Gait Classification and Recognition"*, Proceedings. of The International Conference on Electronics and Software Science 2015, Japan, pp. 87-97, 2015

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- Dipak. Gaire. Sharma, Rahadain Yusuf, Ivan Tanev, and Katsunori Shimohara, *"Human Gait Analysis Based on Biological Motion and Evolutionary Computation",* Proc. of 20th International Symposium on Artificial life and Robotics 2015,Japan, pp.36-39

- Dipak Gaire. Sharma, Rahadian Yusuf, Ivan Tanev, and Katsunori Shimohara, *"Human Recognition via Gait Features and Genetic Programming"*, International Conference on Artificial Life and Robotics, 2014

Patents

- Ivan Tanev, Katsunori Shimohara, and Dipak Gaire Sharma, *Method of Estimating the Inadequate Cognitive Load of Drivers (English Translation)*, Reg.No: 2016-058245, Doshisha University, Kyoto, Japan, March, 2016

- Ivan Tanev, Katsunori Shimohara, and Dipak Gaire Sharma, *Method of Estimating Steering Wheel Vibration Induced during driving of a Vehicle (English Translation),* Reg.No: 2017-094443, Doshisha University, Kyoto, Japan, May, 2017